

METHODS AND TOOLS FOR OPTIMISATION OF OPERATIONAL RELIABILITY AND CONDITION MONITORING OF LARGE-SCALE INDUSTRIAL WIND AND TIDAL TURBINES

By

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Abstract

Industrial wind and tidal turbines are complex systems consisting of several different components and subsystems. Many of wind and tidal turbines use gearbox in their systems that is one of the most important components in the system. Gearboxes are designed to operate for the entire lifetime of a wind or tidal turbine or the equivalent of 20 years. However, very few gearboxes do achieve their intended lifetime without significant refurbishment or even replacement at least once or twice within this 20-year period.

Offshore wind turbine in particular, suffer from relatively high gearbox failure rate due to the harsh sea environment. Any unpredicted gearbox failure in the wind or tidal turbines can results in considerable downtime as a result of limited access caused by weather condition. This results in loss of energy production and excessive maintenance costs that increases the total energy production costs. A reliable and effective condition monitoring system can play a significant role in reduction of operation and maintenance costs by providing early fault diagnostics and consequently longer time frame for planning required maintenance and repairs. Thus, preventing catastrophic failures due to unpredicted gearbox damages.

This study presents an experimental investigation assessing the effectiveness of acoustic emission and vibration analysis in identifying different types of defects in wind and tidal turbine gearbox with means of advanced signal processing techniques, such as Spectral Kurtosis, Kurtogram analysis, Empirical Mode Decomposition and cyclo-stationary analysis to assess their effectiveness.

Advanced machine learning techniques such as support vector machine (SVM) and artificial neural network (ANN) are also explored to evaluate the possibility of the fault

detection using existing Supervisory Control and Data Acquisition (SCADA) condition monitoring data. Finally, combination of advanced signal processing techniques are employed to enhance the fault detection, by removing signal contamination and extraction of hidden features in the vibration and acoustic signal for better fault detection.

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This thesis is dedicated to

my beloved mother, Manijeh Pourakhlaghi.

For her endless support, encouragement and unconditional love.

I love you

and I appreciate everything you have done for me.

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List of Abbreviations

AC	Alternative Current.
ADC	Analogue to Digital Convertor.
AE	Acoustic Emission.
ANC	Adaptive Noise Cancellation.
ANN	Artificial Neural Network.
BPFI	Ball Pass Frequency Inner Race.
BPFO	Ball Pass Frequency Outer Race.
BSF	Ball Spin Frequency.
BSM	Bottom Structure Mount.
CBM	Condition based maintenance.
CF	Crest Factor.
CM	Condition monitoring.
CMS	Condition Monitoring System.
CS	Cyclo-stationary.
CSC	Cyclic Spectral Coherence.
DAQ	Data Acquisition.
DC	Direct Current.
DFIG	Doubly Fed Induction Generator.
DFT	Discrete Fourier Transform.
DSP	Digital Signal Processing.
EEMD	Ensemble EMD.
EMD	Empirical Mode Decomposition.
FD	Fourier Domain.
FFT	Fast Fourier transform.
F_s	Sampling Rate-Frequency Sampling Rate.
FSM	Floating Structure Mount.
FTF	Fundamental Train Frequency.
GAPF	Gear Assembly Phase Frequency.
GMF	Gear Mesh Frequency.
HAWT	Horizontal axis wind turbine.

HFRT	High Frequency Resonance Technique.
HSS	High Speed Shaft.
IFT	Inverse Fourier Transform.
IMF	Intrinsic Mode Function.
IMS	Intermediate speed.
KPI	Key Performance Indicator.
LIDAR	Light Detection And Ranging.
LSS	Low Speed Shaft.
MCKD	Maximum Correlated Kurtosis Deconvolution.
MED	Minimum ENtropy Deconvolution.
MW	Megawatt.
NDT	Non-destructive test.
NSM	Near-Surface Structure Mount.
O&M	Operation and Maintenance.
RAMS	Reliability, availability, maintainability and safety.
RCC	Remote-Control Cernte.
RCM	Remote Condition Monitoring.
RMS	Root Mean Square.
ROC	Recieving Operating Characteristic.
RPM	Revolution Per Minute.
RTU	Remote Trminal Unit.
SANC	Self-Adaptive Noise Cancellation.
SCADA	Supervisory Control and Data Acquisition.
STFT	Short Time Fourier Transform.
SVM	Support Vector Machine.
SVN	Support Vector Network.
TD	Time Domain.
TSA	Time synchronous averaging.
VA	Vibration Analysis.
VAWT	Vertical axis wind turbine.
VFD	Variable Frequency Driver.
WT	Wind Turbine.

*“Science is the knowledge of consequences,
and dependence of one fact upon another.”*
— Thomas Hobbes

Chapter 1

Introduction

One of the most challenging problems currently facing humanity is global warming and its effects on economic and societal stability of the European Union and the rest of the world. The growth in harvesting energy from renewable sources in recent years has proven to contribute substantially into the reduction of greenhouse gas emissions. In particular, wind energy harvesting technology has been developed considerably over the past decade as illustrated in Figure 1.1 and has been one of the main sources of renewable power generation. Wind energy together with hydroelectricity are the most important renewable energy sources currently exploited within Europe. Figure 1.2 illustrates the growth in renewable energy in comparison with other energy sources in Europe over the past decade.

While offshore wind energy has expanded rapidly, tidal energy is yet to be exploited widely at utility scale. This is largely due to the fact that tidal energy still faces considerable technical challenges that need to be addressed before widespread commercialisation can be realised. Nonetheless, governments, policy makers and investors have shown significant interest in tidal energy and therefore in the medium to long-term future this technology is expected to grow considerably [1]. Figure 1.3 compares the annual installation capacity of offshore and onshore wind turbines over the past decade in Europe.

Due to the limited industrial experience with tidal energy systems, the construction, operation and maintenance costs of tidal turbines are higher than offshore wind tur-

bines [2]. Nonetheless, as the learning curve is gradually overcome, it is expected that costs associated with tidal turbines will be reduced to similar levels to those of offshore wind turbines.

Technology and market analysis and forecasts has predicted that by 2050 the wind energy plays a significant role in energy production and will provide more than 36% of the total renewable energy supply [3]. comparison between different sources of renewable energy forecasted for 2050 is presented in Figure 1.4.

As the size and complexity of industrial wind and tidal turbines are increasing, operation and maintenance (O&M) strategies become more complicated and costly. It is important that the O&M strategy is optimised to ensure the highest reliability, availability, maintainability and safety (RAMS) levels possible, hence increasing profitability.

Regular inspection and service schedules can evidently increase the lifespan and operation time of wind and tidal turbines. However, given the size of the wind and tidal turbine farms and their limited accessibility due to the remote locations where they are constructed, it becomes very expensive and impractical to inspect the turbines by manual means on regular basis.

The use of Remote Condition Monitoring (RCM) techniques for diagnosis of damage and prognosis of damage evolution and possible failure can contribute profoundly towards the avoidance of unexpected downtime of offshore wind and tidal turbines without the requirement of deploying inspection engineers and technicians on-site [4]. The drive-train is a critical mechanical subsystem in both wind and tidal turbines being responsible for transmitting the kinetic energy of wind harvested by the blades of the rotor to the generator in order to produce electric power. Drive-trains, particularly the gearbox assembly in geared wind and tidal turbines, are prone to develop damage much earlier than predicted by existing designs. This largely occurs due to the variable loads and operating conditions that wind and tidal turbine rotating components experience, resulting in instant shaft misalignments and inconsistent lubrication quality leading to excessive stresses and higher friction coefficients. The cost of the drive-train in geared offshore wind and tidal

turbines typically equates to 15%-20% of the total cost [5].

Global Renewable Power Capacity, 2007-2017

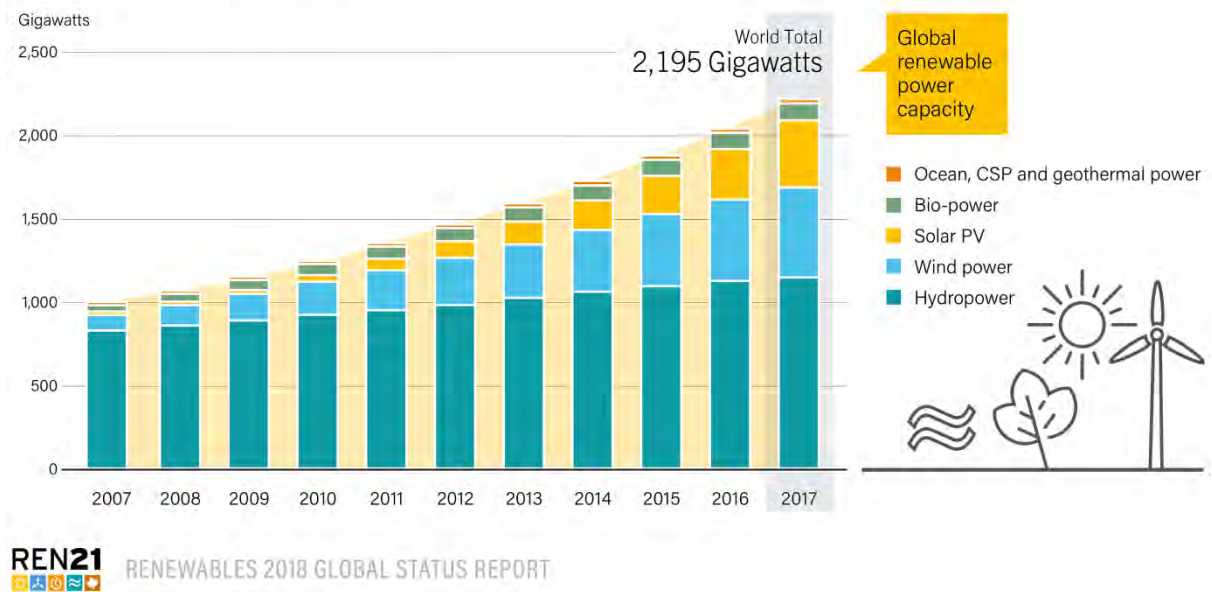


Figure 1.1: Global renewable power capacity growth over the past decade [6]

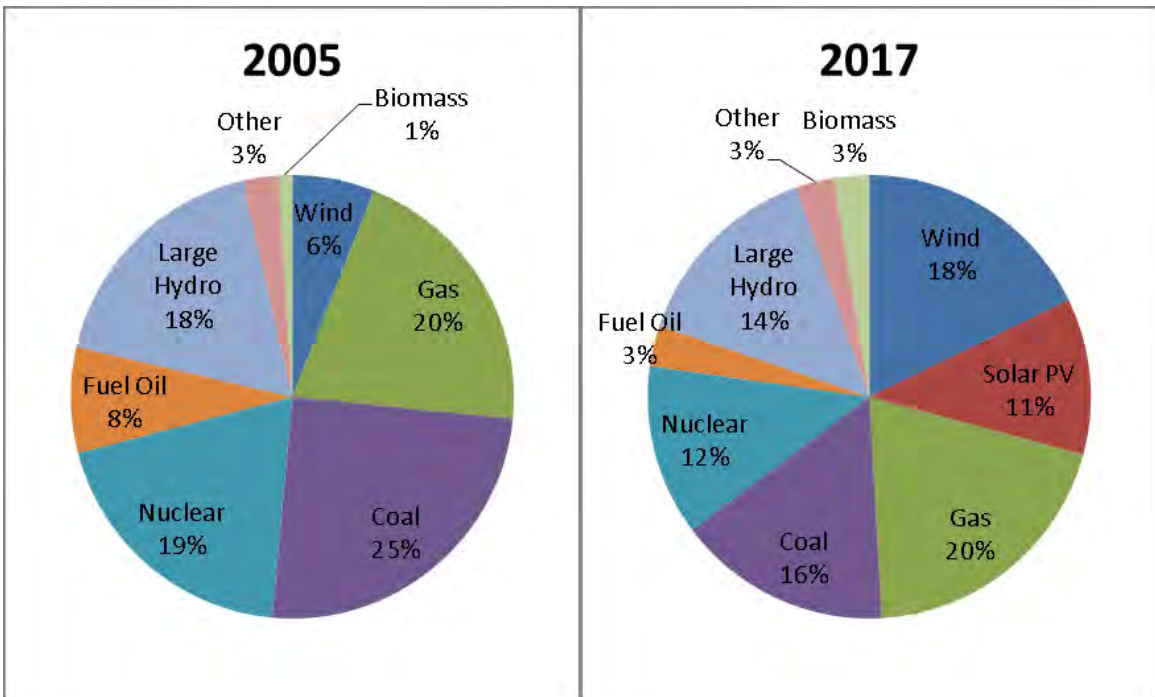


Figure 1.2: Growth in renewable energy in comparison with other energy sources in Europe over the past decade [7]

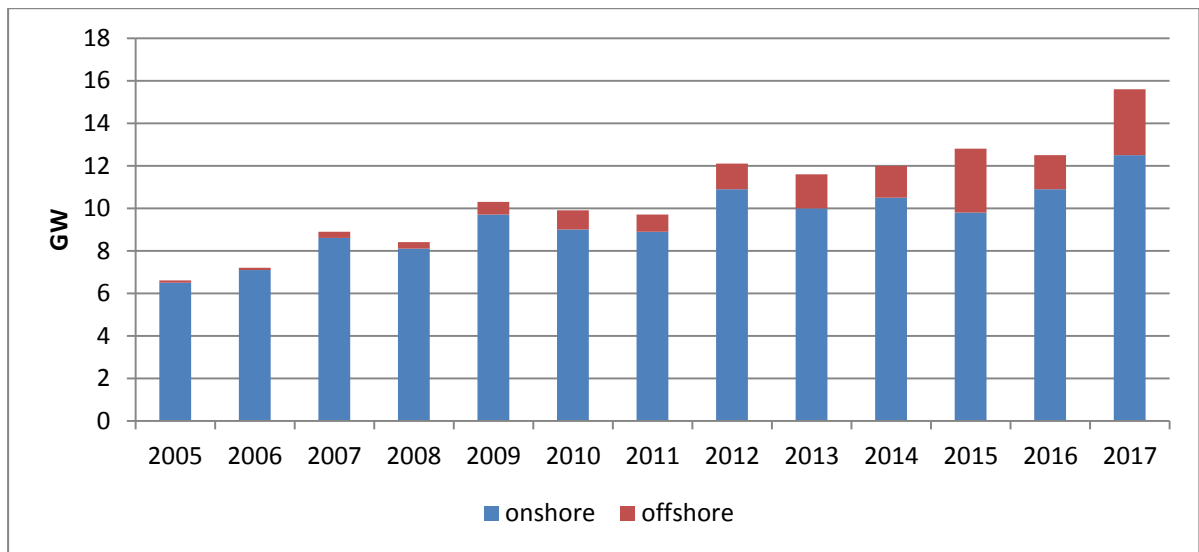


Figure 1.3: Annual installation capacity of offshore and onshore wind turbines over the past decade in Europe [7]

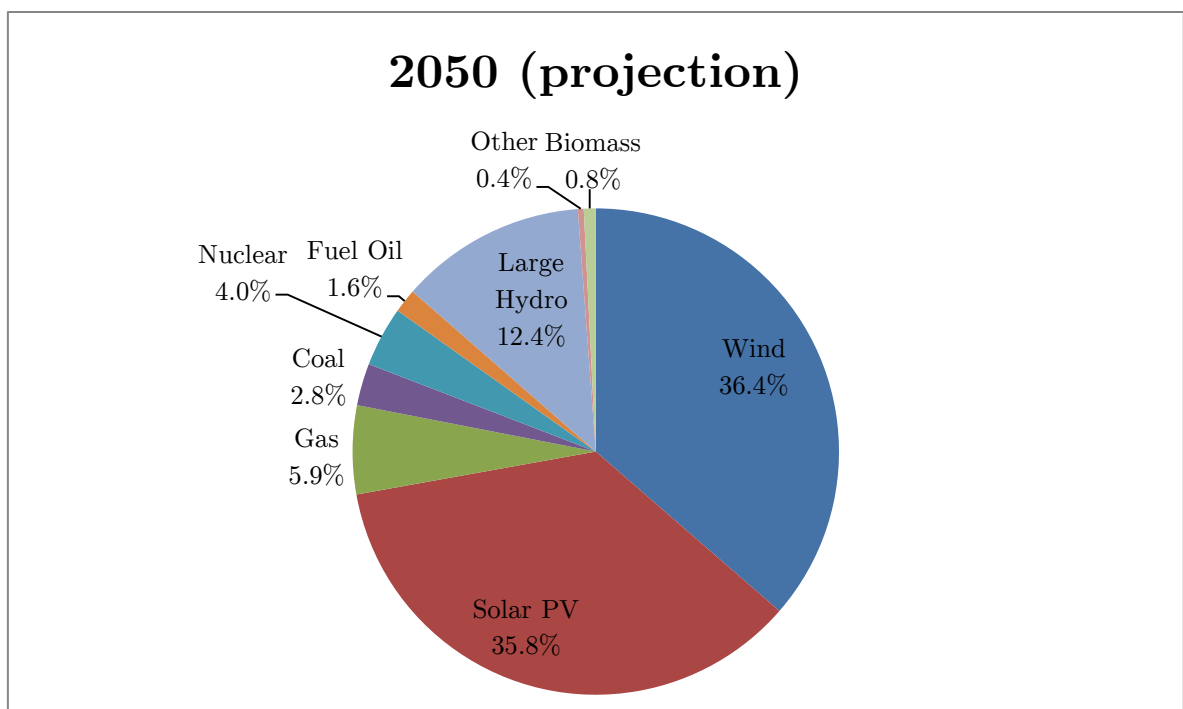


Figure 1.4: Contribution of different energy sources to the global electricity production by 2050 [3]

Nevertheless, as the wind and tidal turbines become more and more complex, and due to their continuously varying operational characteristics, the application of accurate and reliable quantitative RCM and fault detection still poses considerable challenges. Unlike simple gearboxes and steady-state machines, the vibration signal recorded from the gearbox of a wind turbine is contaminated with various unwanted artefacts or noise. The complex nature of gearboxes itself, incorporating shafts, gears and bearings can result in certain defects being masked by other faults. Thus, the detection of a developing fault in its early stages remains particularly challenging using conventional signal processing techniques such as FFT or enveloping techniques.

1.1 Aims and objectives

Condition monitoring of wind and tidal turbines is an essential need to maintain reliability, avoid the occurrence of unexpected faults and reduce maintenance costs by detecting and quantifying the severity of developing faults, taking the necessary actions for repair.

However, having large amount of data recorded from the wind or tidal turbines is impractical as the high bandwidth data link will incur additional costs and processing all the collected data will be very time consuming, requiring very high computational power increasing operational costs. Thus, it would be of desire to obtain maximum information and reliability from minimum amount of data collected from the wind or tidal turbine.

The aim of this project is to explore and evaluate the available tools and techniques to extract the maximum information from the condition monitoring data recorded from wind and tidal turbines. To achieve this aim, various tests on defective bearings and a mock-up gearbox have been carried out in the laboratory whilst several wind turbines have been instrumented and monitored in the field. These can be summarised into the following objectives:

- Review of the various faults developing in the wind and tidal turbines, their causes and prevention techniques.

- Review of the current condition monitoring techniques and the limitation of current techniques.
- Advanced signal processing techniques and methods performed on vibration and acoustic signals.
- Developing a customised software in MATLAB for advanced acoustic emission and vibration signal processing.
- Laboratory and controlled environment experiments on rolling elements (bearings) with known defects.
- Measurements on mock-up tidal turbine with known defects.
- Field trials and measurements on industrial full-size wind turbines.
- Fault detection using existing Supervisory Control and Data Acquisition (SCADA) condition monitoring data by the means of machine learning and data classification.
- Enhancement in fault detection using combination of advanced techniques.

Each of these objectives are detailed and discussed in the forthcoming chapters and concluded in the final chapter.

1.2 Main contributions

The findings in this research will help understanding the abilities and limitation of various signal-processing techniques on prediction and detection of existing or developing faults in the gearbox of large-scale industrial wind and tidal turbines. This Yields a more efficient condition monitoring to achieve optimum fault detection.

These findings will directly help the wind and tidal industry to predict the faults earlier, and consequently avoid any unwanted catastrophic failure or prolong downtime due to unexpected or cascaded damage that will negatively affect the power generation capacity and the stability of the wind farms and tidal turbines.

Having a more efficient and effective condition monitoring will expand the life expectancy of the turbines and provides a longer time frame for the operators to plan for any maintenance. In particular, this is very crucial for tidal turbines due to access limitations caused by environmental conditions.

1.3 Structure of the thesis

The general structure of this thesis is shown in Figure 1.5. The thesis starts by exploring the background, current technologies, systems and subsystems of wind and tidal turbines. Then it progresses into turbine models, their reliability, advantage and disadvantages. Next condition monitoring tools, various sensors and signal processing techniques are explored while progressing to laboratory testing of using customised test rigs under known conditions.

The knowledge gained from laboratory testing is then further advanced and real wind turbines are investigated together with the performance of the condition monitoring techniques to detect the faults in the real wind turbines are evaluated. Finally, SCADA data classification using machine learning is used to detect wind turbine faults and the combination of advanced condition monitoring techniques are utilised to reveal hidden features in the signal.

1.4 Thesis outline

The present doctoral thesis has been organised in 8 chapters. The layout of the remainder of this thesis is as follows:

Chapter 2 surveys the literature on various wind and tidal turbine technologies, taxonomies, systems and sub-systems to provide a better understanding about the turbines and their structures.

Chapter 3 provides more details about the structure of the wind turbines and describes gearbox reliability, comparing geared and gearless wind and tidal turbine designs. This

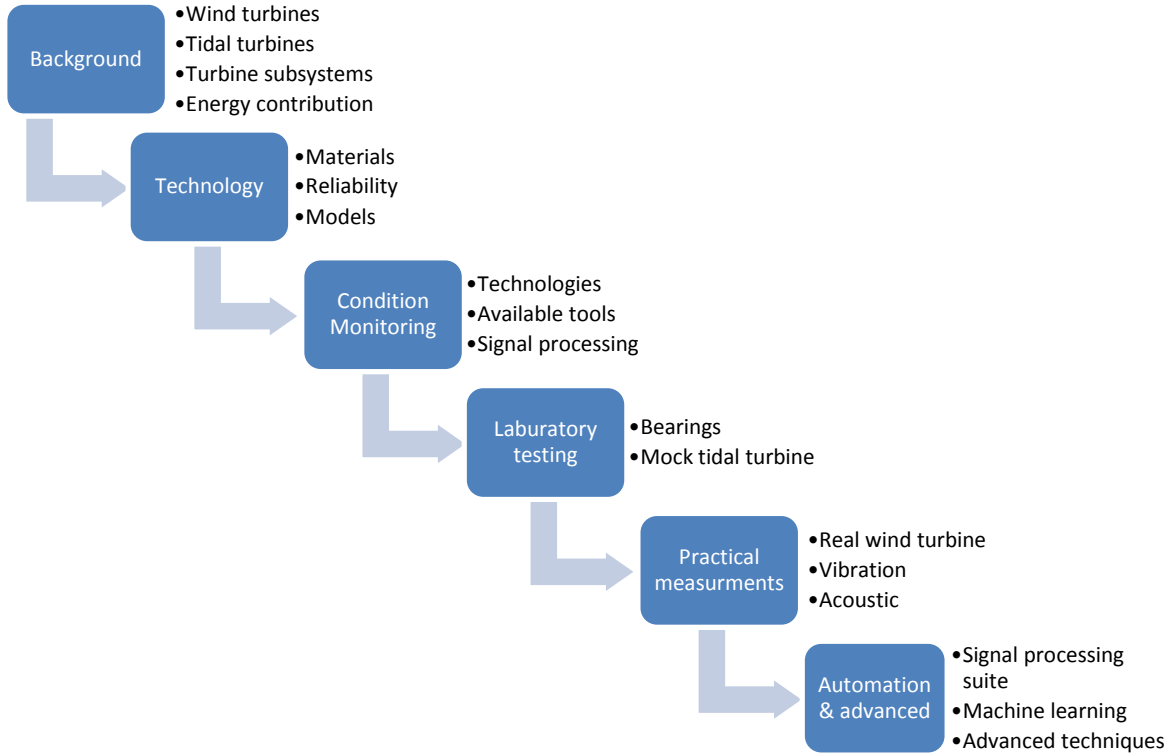


Figure 1.5: The structure of this thesis

chapter looks closely at the wind turbine drive-train, modular structure of the gearbox, planetary gears, roller and ball bearing, gearbox materials and different gear failures. Different types of gears are discussed in this chapter together with common gearbox failure modes. The significance of the gearbox and gearbox reliability and its life expectancy are also discussed as part of this chapter.

Chapter 4 explores signal processing techniques used to analyse acoustic emission and vibration analysis data to detect developing faults in the gearbox of the turbines. Possible condition monitoring methods for the gearbox of wind and tidal turbines are also discussed as part of this chapter.

Chapter 5 presents the results obtained from tests on a bearing test rig developed at the University of Birmingham and a tidal turbine test rig developed at Brunel University. Results from the bearing test rig during non-stationary loading and different operating speed conditions are presented. In this chapter the possibility of the detecting faults in

the bearing and mock tidal turbine using studied signal processing in the previous chapter is investigated.

Chapter 6 describes the methodology used for the evaluation of three full-scale wind turbine gearboxes having sustained misalignment, bearing damage, gear damage, and had been studied using various condition monitoring and signal processing techniques described in the previous chapters. This chapter evaluates the effectiveness of these techniques in detecting the faults in industrial scale wind turbines.

Chapter 7 introduces a MATLAB application and its feature for automatic fault detection. Based on the test rig evidence, different algorithms for automatic defect detection and diagnosis are introduced, mathematically defined, and then applied to analyse the test rig results. This automation software can reduce the complexity and time required to perform signal processing and condition monitoring on large datasets considerably and reduces human error. This chapter also explores advanced condition monitoring and machine learning techniques to identify hidden and early stage developing faults and proposes an enhanced signal processing chain to detect faults invisible to other condition monitoring techniques.

The conclusion of this research project is discussed in Chapter 8 along with suggestions on further work based on the knowledge gained from this project, including improvements in test rig configurations and potential new areas for investigation.

“We are not makers of history. We are made by history.”

— *Martin Luther King, JR.*

Chapter 2

Wind and tidal stream turbines

2.1 Introduction

Renewable energy is obtained from natural sources which are sustainable and reproducible such as wind and solar energy as described by Twidell and Weir [6]. In contrast to non-renewable energy produced from finite sources of energy such as fossils and oil, renewable energy is inexhaustible. The primary source of renewable energy is solar radiation which can be harvested directly using photovoltaic panels or indirectly from the wind using wind turbines. However, there are also renewable energies caused by non-solar sources such as tides which are originating by gravitational interactions with the moon.

The use of wind goes back to the ancient age when people started to use sailing boats and wind mills for grinding flour. The very first evident use of tidal energy goes back to the 6th century AD where a water mill was powered by a tidal stream [8]. Evidence showing energy harvesting from tide as early as 10th century AD are available, when people were building and using tide mills [9]. One good example of these tide mills which is still in working condition is the Woodbridge Tide Mill located in Suffolk, England, built in 1170 [9].

This chapter will briefly review the history of wind and tidal turbines and look at different types of turbines including horizontal and vertical axis turbines. Then the con-

tribution and popularity of each type of wind and tidal turbine are reviewed followed by system breakdown.

2.2 Early turbines

Although renewable energy has been in use over all this time, it was not until the 18th century AD that wind power was used to produce electricity. The first known wind turbine was built in 1887 in Scotland by Professor James Blyth of Anderson's College in Glasgow. However, for tidal turbines for generating electricity were not considered until much later in the 20th century [10].

The early tidal stream electricity generators were based on a barrage design in the form of a dam with a basin that was filled during the tide and then emptied through the generator during ebb duration. An example of this type of structure is the La Rance barrage in France, built in 1967 with a capacity of 240MW and which is still in operation today [10]. Table 2.1 lists the four largest tidal turbine systems that are currently in operation. The problem with tidal barrages is their significant impact to the environment [11]. They can be dangerous for aquatic animals such as fish and dolphins or even whales. There has been one report in 2004 that a whale was trapped in the basin of the Annapolis barrage turbine located in Canada [12]. Despite technological advances, even the most fish friendly turbines are still dangerous to aquatic animals, resulting in increased mortality [13, 14]

Table 2.1: The 4 largest barrage type tidal turbines in the world that are still in operation.

Location	Site	Basin area (km ²)	Mean tide level (m)	Turbine capacity (MW)	Installation year
France	La Rance	22	8.55	240	1967
Russia	Kislaya Guba	1.1	2.30	0.4	1968
Canada	Annapolis	15	6.40	18	1984
China	Jiangxia	1.4	5.08	3.9	1985

2.3 Modern wind and tidal stream turbines

Tidal stream generators are very similar in nature to wind turbines. Tidal turbines are large-scale rotating systems consisting of several subcomponents. They are designed to efficiently convert the kinetic energy of water to electrical energy through the transmission of torque to the generator.

The typical design of commercial industrial tidal turbines is very similar to offshore wind turbines. Tidal turbines are installed underwater in rows like wind farms. The advantage of tidal turbines in comparison with wind turbines is the fact that operation is independent of weather and climate changing, with tides being predictable from the lunar orbit. Moreover, due to the density of water which is 800 that of air, energy harvesting is more efficient in terms of the rotor size required to harvest the equivalent amount of energy. However, due to the much higher stresses sustained by the blades in the water their length is much smaller whilst rotor speed is only a few RPM. Due to the limited industrial experience with tidal energy systems, their construction, operation and maintenance costs remain higher than those of offshore wind turbines [2]. Nonetheless, as the learning curve is gradually overcome it is expected that costs associated with tidal turbines will be reduced to similar levels to those of offshore wind turbines.

Currently, there exist more than thirty different types of tidal turbine which are under different stages of development. One of the most advanced designs is the MCT SEAGEN geared tidal turbine. Geared tidal turbines are very similar to geared wind turbines with the main difference being related to the blade design and the requirement for watertightness of the nacelle.

Tidal turbines like wind turbines are also subjected to variable loads and therefore similar issues with the drive-train, particularly the gearbox, are anticipated. As mentioned earlier, variable loading conditions do affect the lubrication quality increasing considerably fatigue damage accumulation. Instant misalignments due to variable loads or permanent misalignment can further exaggerate fatigue damage resulting in final failure much earlier

than anticipated in the design.

2.4 Tidal stream generators

Tidal stream generators can be grouped into 4 different categories [15] as described below.

- Vertical axis turbines: In this type of turbines the main rotor shaft is transverse to the tidal stream. This can be set up either vertical or horizontal but in a transverse direction. In this type of design, the gearbox and generator can be at the bottom near the seabed or at the side of the river or water stream.
- Polo turbines: This type of turbines usually have a vertical axis and their structure is similar to hamster wheels with the blades on the circumference of the wheel. This type of design can have variable pitch blades.
- Venturi effect turbines: This type of turbines is based on the Venturi effect produced with a duct narrowing in the centre to accelerate the tidal flow. The generator in these turbines is located in the centre of the duct for maximum efficiency.
- Horizontal axis turbines: Unlike vertical axis turbines, in this type of design the main rotor shaft is pointing towards the tidal stream. This is very similar design to horizontal axis wind turbines (HAWT) but fully submerged in the water.

An example from each of these types is presented in Figure 2.1. Recently, a new type of tidal turbine was prototyped by BioPower Systems which is based on oscillating hydrofoil technique, having a motion similar a fish tail fin. Figure 2.2 illustrates this rather different design.

Despite the availability of these different types of tidal stream turbine, reviewing 76 available systems by Khan, Bhuyan [19] shows that the horizontal axis turbines are the most popular type of tidal stream turbines with 43% and the vertical axis turbines are in second place with 33%. Figure 2.3 illustrates contribution of all different types of turbines.

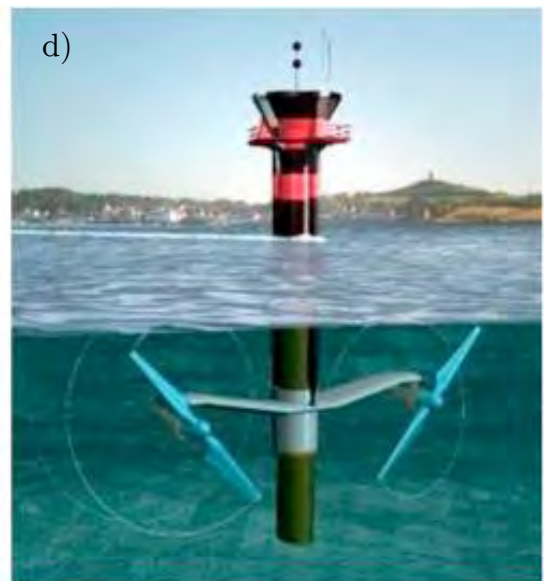
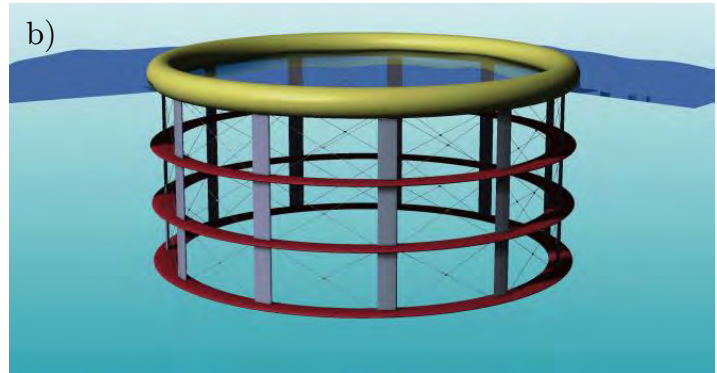
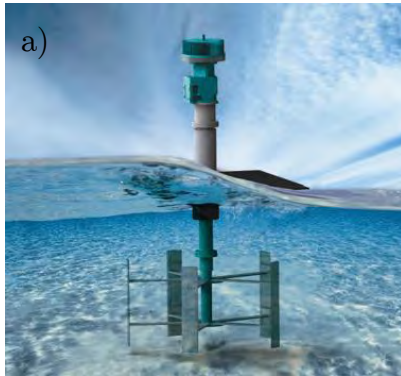


Figure 2.1: Different types of tidal turbines; a) Horizontal axis; b) Polo turbines; c) Venturi (duct) effect; d) Horizontal axis [16–18]



Figure 2.2: Oscillatory-hydrofoil turbine concept, developed by BioPower System company [17]

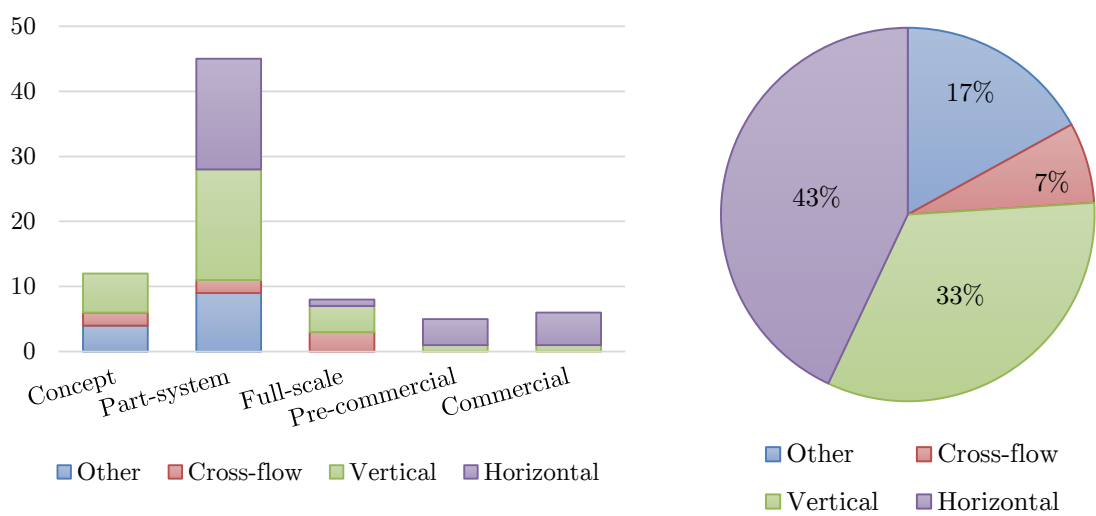


Figure 2.3: Technologies used in tidal turbines [19]

A tidal stream generator can be divided into several general sub-systems and sub-assemblies. Figure 2.4 shows a generalised chart summarising tidal turbine configuration. Some of these main sub-assemblies will be discussed next.

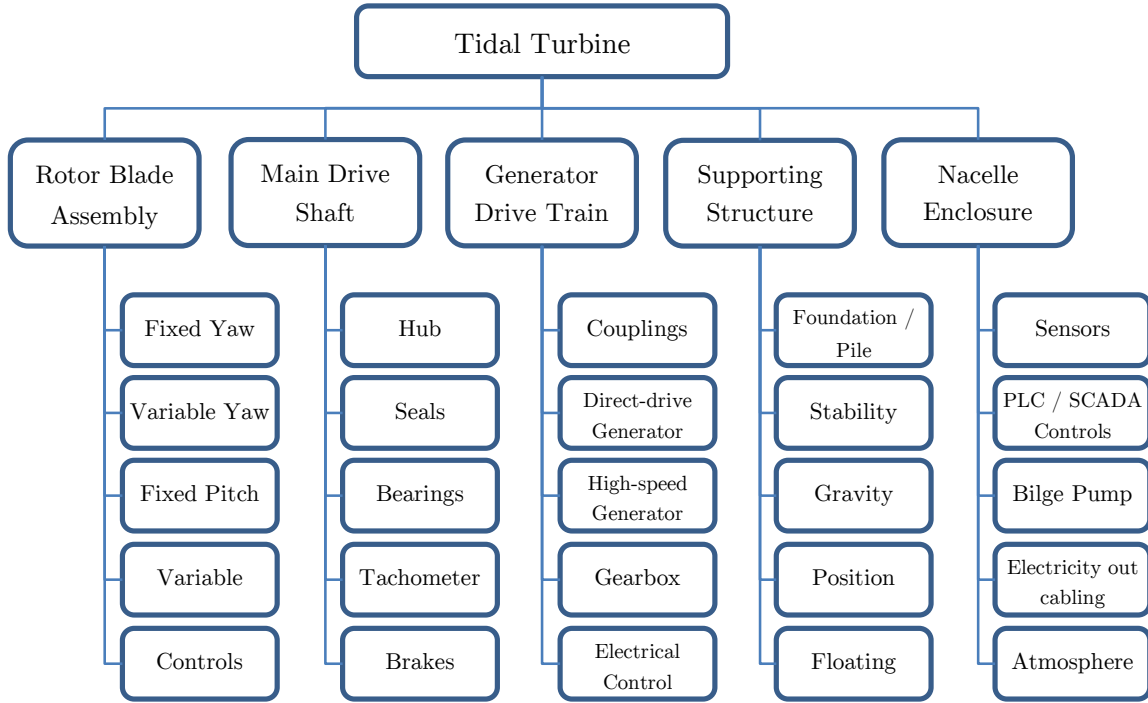


Figure 2.4: Generalised tidal turbines configuration [20]

2.4.1 Rotor blades

This is one of the crucial sub systems in the tidal turbines. The tidal stream will directly act on the rotor blades, forcing the blades to turn the rotor shaft, producing rotational kinetic energy which then will be transferred by the drive train and will be converted into electrical power. The blades can move in single direction with fixed pitch or the blades pitch might be variable and change depending on the amount of tidal stream. They can also be bi-directional with variable pitching enabling the blades to turn in both directions depending on the tidal stream direction to maximise the energy production. Unlike wind turbines, the forces applied on the tidal rotor blades are much greater due to the much higher density of water which is 800 times that of air. Table 2.2 compares some of the

turbine parameters between similar horizontal-axis 1MW wind and tidal turbine. As it is shown the thrust in tidal turbine can get twice as big compared to the equivalent wind turbine. Furthermore, the tidal blades can significantly suffer from erosion by solid particles, fouling by marine growth, corrosion and erosion-corrosion [21]. Failure of the rotor blades in a tidal turbine has much more serious consequences compared with wind turbines. Due to the hostile underwater conditions and limited available time windows caused by poor weather condition, retrieval and recovery operations of tidal turbines can take considerable amount of time and effort. Similar to the wind turbines, the material of choice for the blades in tidal turbines is glass or carbon fibre reinforced plastics [22]. Several recent failures in tidal turbines have been attributed to blade failure [23]. There are various blade monitoring techniques such as acoustic emission, fibre-optic or strain gauge measurement sensors which can be employed for monitoring blades. Also a number of methods for biofouling prevention and corrosion resistance have been applied but there is still a need for methods which help minimise impact damage events by monitoring their occurrence [21].

Table 2.2: Comparison between similar wind and tidal turbine parameters (1MW power rating) [21]

Parameter	Wind turbine	Tidal turbine
Medium density (kg/m^3)	1.2	1000
Rotor diameter (m)	52	20
Number of blades	3	2 – 5
Rotational speed (r.p.m)	7 – 2000	7 – 20
Velocity of maximum power (m/s)	12 – 13	2.5
Mass flow rate (tonnes/s)	30 – 40	900
Thrust (tonnes)	50	100

2.4.2 Drive-train

The drive-train is one of the main systems of the tidal turbine consisting of three sub-systems including, the rotor shaft, gearbox and generator. The main objective of the drive-

train is to transfer the torque produced in the rotor blades into the rotating generator in order to convert it into electrical power. Each of these sub systems will be briefly described below.

Gearbox

The gearbox in tidal turbines translates the high torque low-speed drive shaft energy arising from the rotational motion of the rotor, into high-speed low torque energy which will drive the generator to generate power. The speed required by the generator varies depending on the required grid electricity and frequency. This is very similar to wind turbines. However, the gear ratio is usually higher than the wind turbines as the rotor speed is slower in the water but has higher torque. A typical low MW wind turbine gearbox can have three stages, one planetary and two helical-parallel stages with a ratio between 60 to 80 [24]. while an equivalent tidal turbine would have a 4 stages gearbox with three planetary stages and one helical-parallel stage with a ratio of about 200 [25]. The gearbox is equipped with a lubrication system to reduce the gearbox early deterioration. It may also be equipped with a breaking system at the high-speed output to reduce the speed and hold the turbine in case of emergency shut-down or maintenance.

Generator

Tidal turbines can employ either a synchronous or asynchronous generator, also known as an induction generator. Asynchronous generators are running above the grid synchronous frequency and are very popular in wind turbines due to their ability to produce power at variable speed. They are simpler compared with other types of turbines, do not require a commutator, are light weight and can withstand adverse operating conditions. However, they require a cooling system. In contrast, synchronous generators are bulkier and heavier than asynchronous generators and running at a lower speed. This will remove the needs for the presence of the gearbox and the generator can run as a direct-drive.

2.4.3 Power converters

To be able to connect the generator to the grid, a power converter is required. The main role of the power converter is to convert the variable frequency from the tidal turbine generator into the grid frequency. This is usually done in 3 steps. A rectifier unit converts the generator alternating current (AC) into direct current (DC) and then feeds it into a DC link capacitor. The DC link capacitor is then connected to a switching inverter, producing a fixed frequency AC current. Figure 2.5 shows a typical AC-DC-AC converter. After conversion, the generated voltage will be fed into a transformer to step up the voltage to several kV in order to reduce the transmission loss and connect the turbine into the grid.

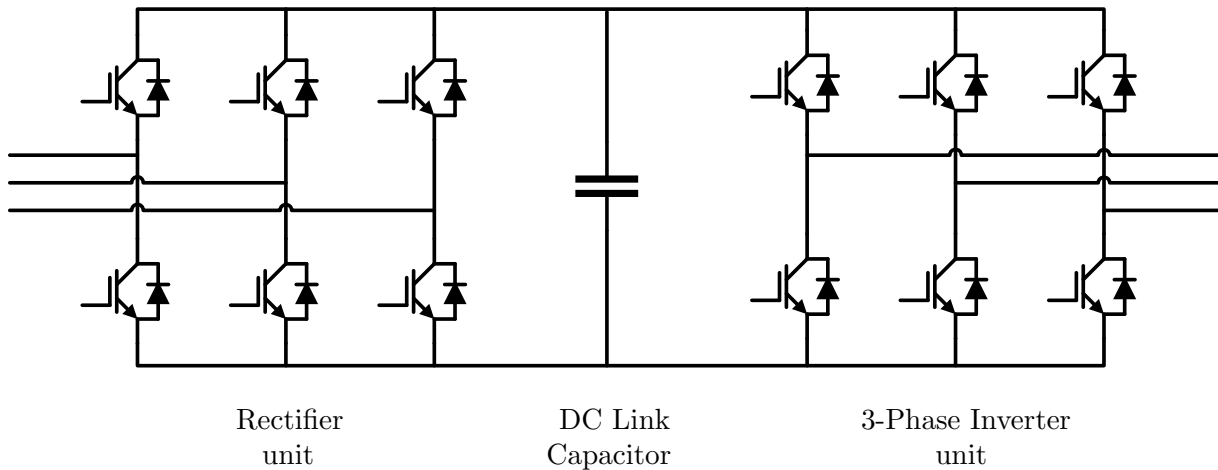


Figure 2.5: A typical AC-DC-AC converter with DC Link Capacitor to translate high frequency generated power into the grid frequency [26]

2.4.4 Low voltage consumable power

Some tidal turbines are required to be powered from the grid before starting to produce power. Additionally, some systems such as the control and safety systems or brakes are required to be powered uninterruptedly even if the turbine is stopped. These units are usually powered from the grid. However, there is usually a second source of power on-board which is supplied from low voltage batteries that are kept charged from the grid. These batteries are providing uninterruptable power to the low voltage electrical systems

of the tidal turbine.

2.4.5 Control and management systems

The control system in the tidal turbine is very similar to the wind turbine control system and as its name suggests, it monitors and controls the tidal turbine operation. This includes but not limited to the amount of tidal flow, the position and pitch of blades, blade and rotor speed and brakes. It also monitors various parameters such as temperature, cooling system, lubrication system and external damage and corrosion level. This system can manage the operation of the tidal turbine independently as well as being managed remotely to shut down the turbine safely in cases such as emergency, planned maintenance or inspection.

2.4.6 Support structure

The forces acting on the tidal turbines submerged beneath the surface are very high and complex. In addition, the rotor develops a high axial force that makes it essential to secure the turbine to the seabed. The supporting structure is responsible for holding the turbine in place against these forces. There are several different types of supporting structures available to secure the wind turbine. These supporting structures can be grouped into two categories, fixed structures using gravity-base or monopile-support structures and floating structures using mooring-support. Figure 2.6 shows few different types of supporting structures used in tidal turbines. Depending on the sea environment, the amount of force acting on the tidal turbine and the type of tidal turbine any of these supporting structures can be used to secure the turbine.

The review on 76 available tidal systems by Khan, Bhuyan [19] shows that Bottom Structure Mounting (BSM) is very popular within horizontal axis turbines while vertical axis turbines are mostly supported using Near Surface Structure Mounting (NSM). Figure 2.7 illustrates these results.

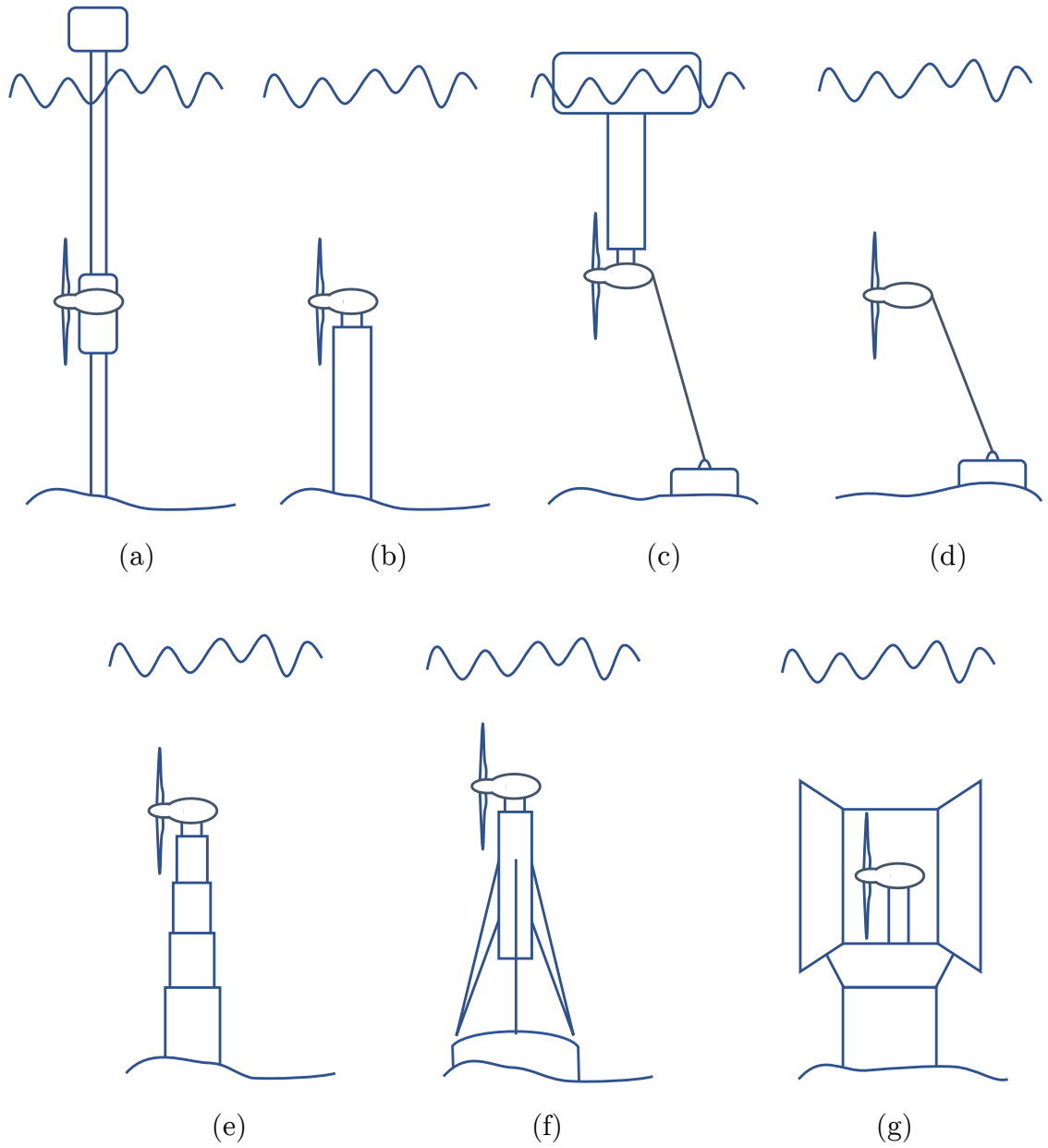


Figure 2.6: Different type of tidal stream turbine supporting structure [27] a) surface piercing seabed monopile; b) seabed mounted monopile; c) floating pontoon; d) seabed tethered; e) telescopic seabed monopile; f) floating SPAR buoy, tethered to seabed; g) ducted seabed mounted.

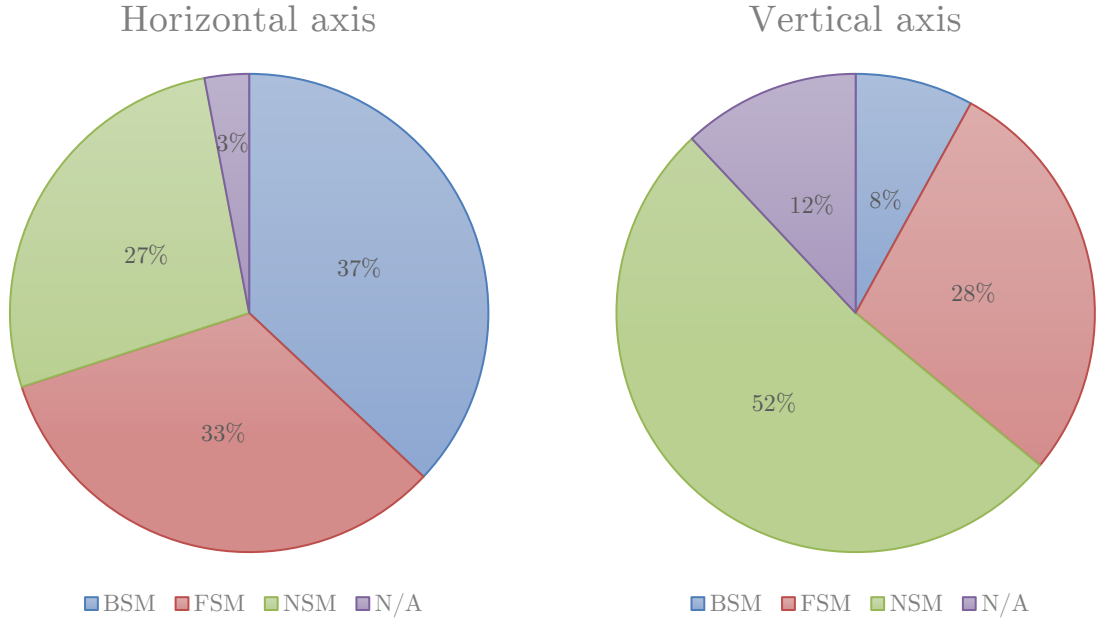


Figure 2.7: Variation of the turbine supporting structure in vertical axis and horizontal axis tidal turbine [19]. These techniques are known as Bottom Structure Mounting (BSM), Floating Structure Mounting (FSM) and Near-surface Structure Mounting (NSM).

2.4.7 Power transmission

One important challenge in tidal turbine operation is the electricity connection link to transfer the produced electricity onshore. One solution is to use fixed cables via seabed, similar to the offshore wind turbines. However, in the case of floating and semi-floating tidal turbines this will be very difficult and usually an umbilical cord will be used from the turbine to the seabed. However, this approach can affect the dynamics of the wind turbine and its floating performance. Apart from the power cables the data cables are also spread alongside the power cables all the way to the shore for remote condition monitoring and controlling. Figure 2.8 illustrates the cross-section of a typical sub-sea cable. Modern tidal turbines are usually designed to work unsupervised, however, there exists a supervisory overriding control to be able to control the turbine in case of emergency or maintenance. The communication between the control unit and offshore management unit is achieved using the data cable. Depending on the generator power ratings and distance of the tidal turbine to the shore there can be an offshore substation (either submerged or floating) in

addition to the subsea transmission line and onshore substation [28].

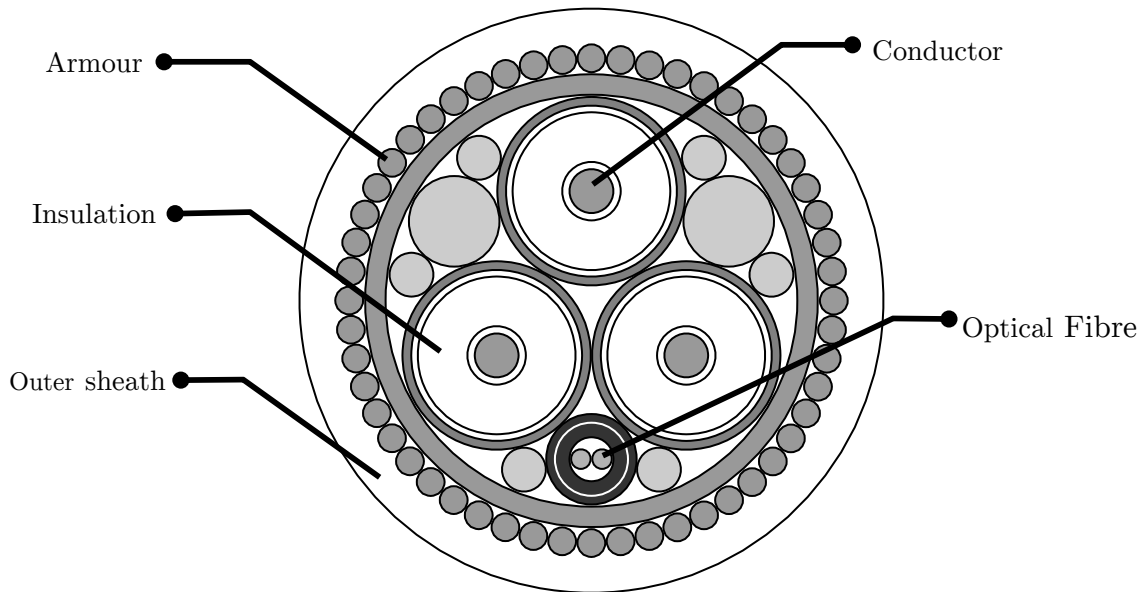


Figure 2.8: Cross-section of a typical subsea cable [28].

2.5 Summary

In this chapter the history of wind and tidal turbines were briefly reviewed. The wind and tidal turbines have been utilised over centuries; however, they are becoming more popular over the last few decades. Different types of wind and tidal turbines and their subsystems were also explored.

In the next chapter the wind and tidal turbine technology and models will be discussed in more depth. Subsequently, the material used in the turbines, damage mechanism and their reliability will be reviewed.

“As far as the laws of mathematics refer to reality, they are not certain, and as far as they are certain, they do not refer to reality.”

— Albert Einstein

Chapter 3

Wind and tidal turbines technology and reliability

3.1 Introduction

In the previous chapter, different types of turbines such as vertical and horizontal axis were discussed. Depending on the type of generator that is used in these turbines, they can be divided further into more sub categories. Each of these sub categories has some advantages and disadvantages that are discussed in this chapter.

This chapter is further reviewing the structure of the wind and tidal turbines, with emphasis on the gearbox, its material and damage mechanism. The characteristic frequencies of the gearbox, its modular structure, related faults and maintenance are also explored.

3.2 Geared and direct drive design

There are two types of turbines, geared and gearless or direct drive turbines. Depending on the type of the generator, the turbine may need a gearbox. Therefore, the design of the gearbox in wind and tidal turbine is tightly linked to the choice of the generator which is the main electrical component of the wind turbine.

There are five different generator systems [29];

- 1) Direct-drive electrically excited
- 2) Direct-drive permanent magnet excited
- 3) Permanent magnet
- 4) Doubly fed induction generator (DFIG) with single stage gearbox
- 5) DFIG with three stage gearbox

Direct-drive designs are very competitive to the geared designs. The idea of this design is to remove the gearbox which is the most complicated mechanical sub-system of the turbine. The bearings and gears in the gearbox experience high levels of stress due to the wind turbulence. Defects in gearbox components can cause failure of the gearbox, causing subsequently wind turbine downtime until the fault has been rectified [29–32]. Figure 3.1 shows an example of gearbox failure. The gearbox can be removed in the wind turbine design if the number of poles is increased from 4 or 6 to 100. From the equation 3.1 it can be seen that by increasing the number of poles the RPM of the generator will decrease respectively [33].

$$rpm_{generator} = 120 \times \frac{f}{n} \quad (3.1)$$

Where, f , is frequency in Hz and, n , is the number of generator poles. Also in direct drive system generator work at lower rotational speed.

According to the data collected by Germanische Lloyd (GL) 26% of turbine downtime is due to the gearbox [34]. Therefore, the gearbox is the most maintenance-intensive component of the turbine especially in offshore wind farms. Although direct-drive designs remove the need for the gearbox, they do require heavier and more expensive nacelles. In addition, the power electronics are more prone to faults in comparison to geared designs.

For gearless wind turbines, permanent magnet generators are more used due to their light weight and increased level of reliability [35].



Figure 3.1: Broken planetary gear in gearbox. Figure taken from [34].

Figure 3.2 shows the two different types of wind turbines. In the geared design the torque produced by the rotor decreases using a gearbox at high gear ratio. Simultaneously, the speed of the output shaft increases with the same ratio adjusted to the high speed generator generating electric power and feeding it to the grid [34].

In direct-drive wind turbines, a high torque generator is used which is directly coupled to the hub and rotor blades. In both designs, power converters enable variable speed of the rotor increasing aerodynamic efficiency [34].

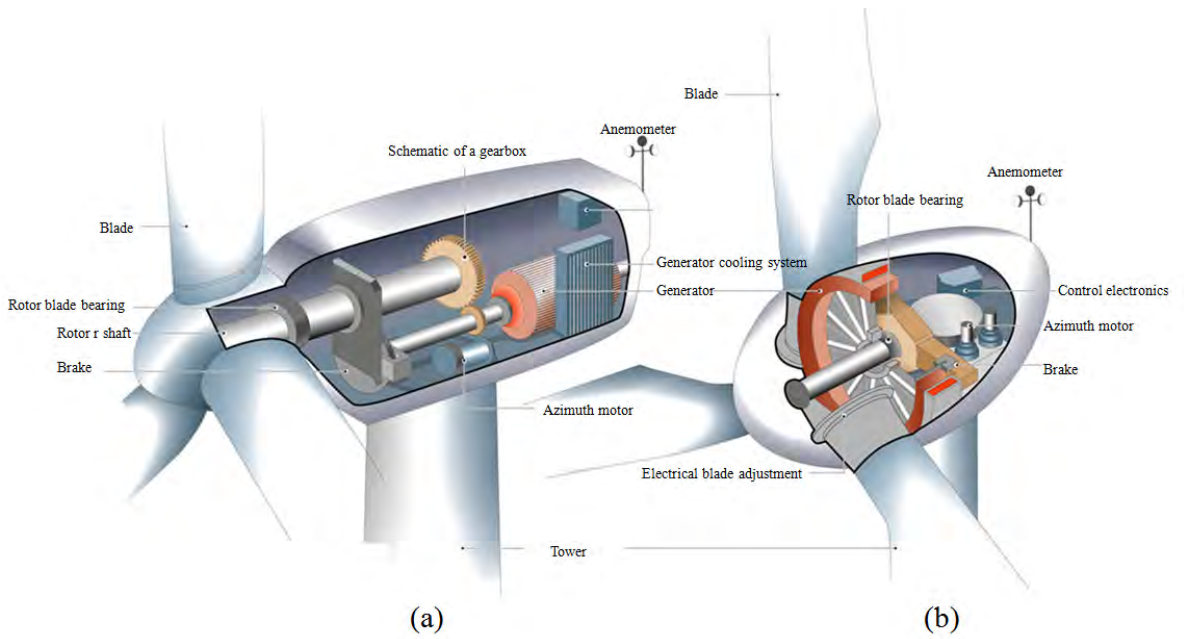


Figure 3.2: Two different design principles (a) Geared design (b) Gearless (Direct drive) design after [36].

3.3 Comparison of geared and direct-drive designs

Table 3.1 provides a comparison between geared and direct drive.

Table 3.2 summarises some examples of gearless models in terms of their output and rotor size.

Table 3.1: Comparison of geared turbine and direct drive turbine.

Geared turbine	direct drive turbine
	
Incorporates a gearbox (three stages normally)	No No gearbox therefore low noise , less maintenance and less losses
Lower rotor speed	Lighter rotor and potentially rotor more noisy due to higher rotational speed but no noise from gearbox
Requires condition monitoring to enable insurance	Less reliable power electronics
Requires maintenance and lubrication	Heavier nacelle
Less magnets required	Ten times more magnets required
Requires hydraulic supply and pump for lubrication	More expensive overall

3.4 Advantages and disadvantages of direct drive turbine compared with geared turbine

According to a number of studies concerning direct-drive turbines [34], down-time due to gearbox defects is irrelevant. However, faults related to power electronics and the increased number of magnets required in the generator results in higher weight and greater costs. The main bearing, generator bearing and main shaft may also develop faults. Hence, faults related to rotating components are not ruled out even in the gearless designs.

Geared turbines at the moment are the predominant type used by the industry [37]. However, there has been a noticeable increase in the use of gearless designs in offshore wind farms in recent years due to the significant gearbox problems faced in early offshore wind turbine designs.

Table 3.2: Gearless wind turbine megawatt power rated and their rotor blade diameter [33].

Company	Country	Turbine Rated Power	Rotor blade Diameter (m)
Clipper (Windpower) Marine deployment date: 2012	UK	10	144
Sway	Norway	10	145
Enercom E-126	Germany	7.5	127
Nordex N150/6000	Germany	6.0	150
Xingtian Electric Manufacturing Corporation	China	5.0	—
GE 4.1-113	United State	4.1	113
GE 4.0-110	United State	4.0	110
Scan Wind 3.5 (evolved into GE 4.X series)	Norway	3.5	90
Enercon E-101	Germany	3.0	101
Leitwind LTW10	Italy	3.0	101
Siemens SWT 3.0-101	Germany	3.0	101
Enercon E-82	Germany	2.0-3.0	83
Guangxi Yinhi Avantis Wind Power (in testing)	China	2.5	—
Vensys 2.5 MW	Germany	2.5	90-100
Enercon E-70	Germany	2.3	71
Leitwind LTW70	Italy	1.7-2.0	70.1
Leitwind LTW80	Italy	1.5-1.8	80.3
MTorres TWT 1.65/70	Spain	1.65	70
MTorres TWT 1.65/77	Spain	1.65	77
MTorres TWT 1.65/82	Spain	1.65	82
Leitwind LTW77	Italy	1.5	76.6
Leitwind LTW86	Italy	1.5	86.3
Vensys 1.5 MW	Germany	1.5	70-82

3.5 The significance of the gearbox in wind and tidal turbine operation

The main task of the gearbox is to multiply the slow input rotational speed of the rotor and transmit it to the generator at much higher speed whilst reducing the overall torque experienced by the generator [38]. Two main types of gearboxes exist in the industry. The first one is the planetary gearbox which has a higher gear ratio in a compact size, therefore reducing the overall mass and volume of the gearbox. The geometrical configuration of the planetary gearbox is advantageous as the input and output have concentric axis with the same rotational direction. Therefore, it is reasonably simple to design a multi-stage planetary gearbox with very compact dimensions as required for a wind turbine application. The second design is the parallel shaft gearbox which is a collection of simple gear stages composed of gear, pinion and two shafts in parallel [39].

The turbine blades are not able to rotate fast enough because they cannot sustain the loads without structural failure becoming likely after a short period of operation. Therefore, a gearbox is needed to increase the slow rotational motion of the blades to the speed which is satisfactory for enabling the generator to produce electricity at the required frequency of 50 or 60 Hz [40,41].

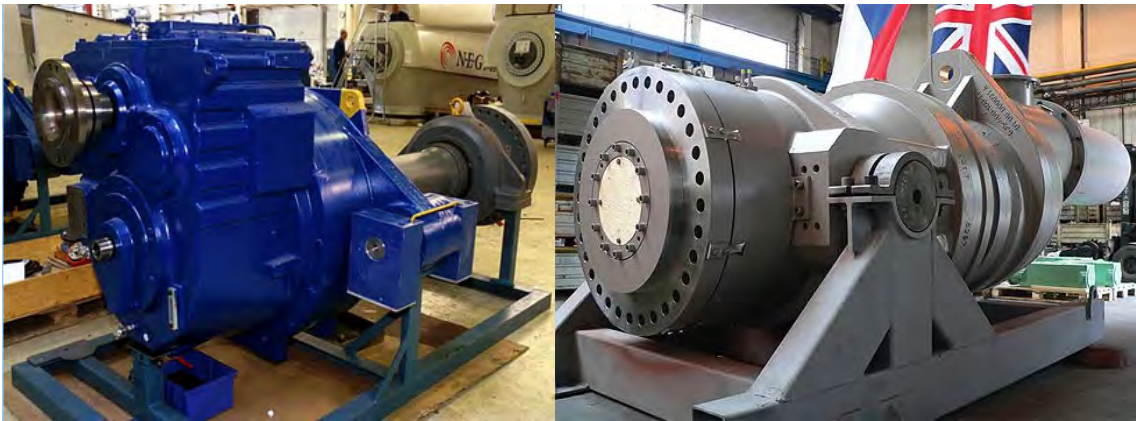


Figure 3.3: Planetary gearbox in wind turbine (Left) [38] and SEAGEN gearbox tidal turbine (right) (photo is courtesy of MCT).

The gearbox of the turbine consists of several types of gears which increase the rotational speed of the rotor by about 50-120 times for large scale industrial turbines [37].

From the economic point of view, having a gearbox in the wind turbine allows the use of a smaller nacelle resulting in cheaper and lighter overall design. In addition, large gearbox bearings will absorb shock, radial and axial loads which the generator needs to sustain in gearless turbines [42].

Different types of gears have been developed as shown in Figure 3.4.

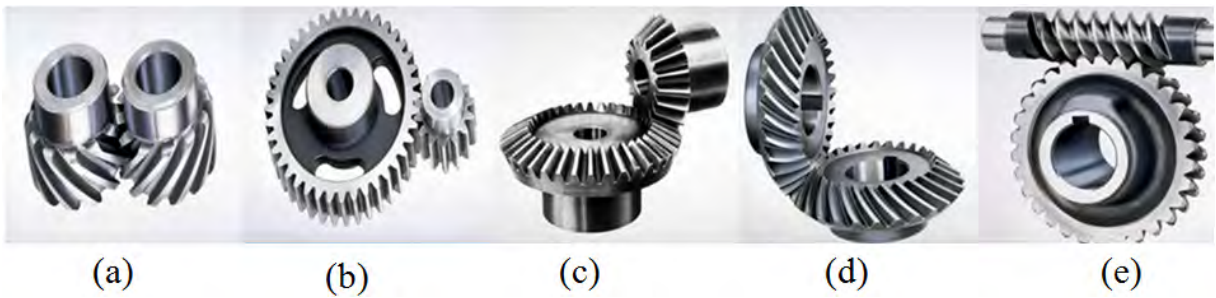


Figure 3.4: Different design of gear (a) Helical gears (b) Spur gears (c) Bevel gears (d) Spiral bevel gears (e) Worm gears after [38].

Helical gears are commonly used in wind and tidal turbine gearboxes. The teeth of the helical gears are cut at an angle to face the gear. In this gear design when two teeth of the helical gear engaged, the contact between teeth starts at one end of the tooth and slowly spreads as the gears rotate until the two teeth are completely engaged [38].

Spur gears are the most common gear design with straight teeth. They are used to generate large gear reduction [38].

Bevel gears are employed if the direction of the rotation of the shaft needs to change. They are mounted on shafts which are placed at an angle of 90° to each other [38].

Spiral bevel gears have gear teeth with curved design. The contact of the tooth starts at one end of the gear and then spreads across the whole tooth [38].

Worm gears are used when large gear reduction is needed. Usually they have 20:1, or even up to 300:1 reduction [38].

Planetary gears are extensively used in wind turbines. In planetary gears, multiple outer gears or planets, rotate the single central gear or sun gear as it is known. In these

types of gears an outer ring which is called annulus is required in order to change the RPM. The annulus is connected to the rotor hub and the sun gear is connected to the generator side [33]. Figure 3.5 shows the details of the simple planetary single stage gear.

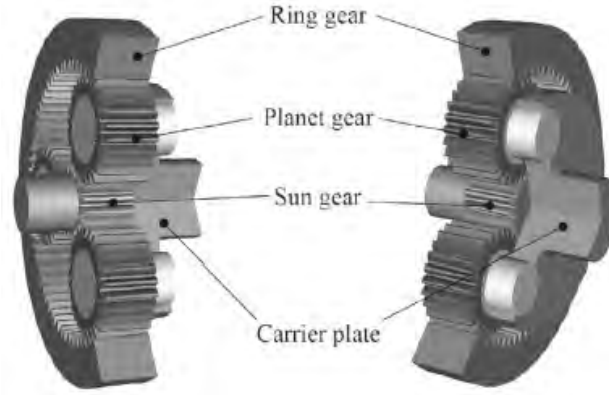


Figure 3.5: Illustration of single stage planetary gear [43].

Planetary gears give the higher power densities in comparison with parallel axis gears. Also they offer several gearing options enabling large change in RPM within a small volume. Besides the advantages they have, the complexity of their design, the amount of high load on shaft bearing can be considered as disadvantages [33]. Figure 3.6 shows the rotational direction of the single stage planetary gear components. It can be seen that the direction of the input and output are the same [39].

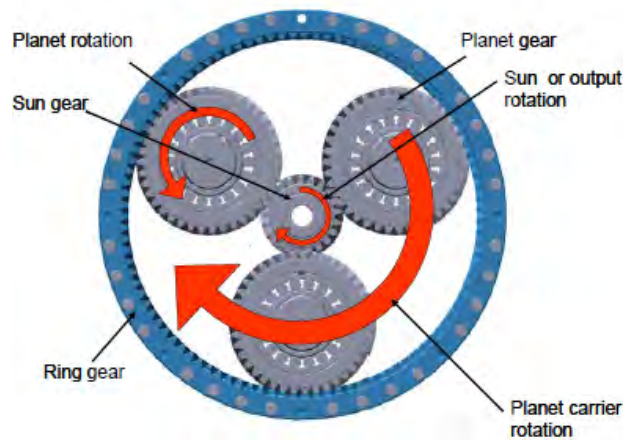


Figure 3.6: Rotational direction of planetary stage gear [39].

Large-scale industrial wind turbines use gearboxes that consist of both planetary and helical gears [37].

Figure 3.7 presents the gear nomenclature.

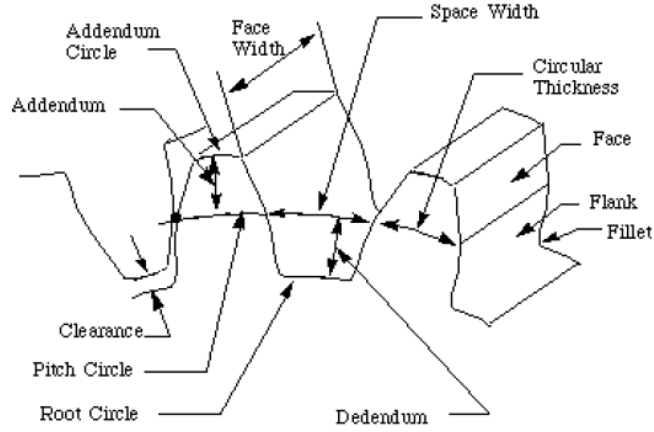


Figure 3.7: Gear nomenclature [44].

3.6 Gear mesh frequency

The typical rate that teeth meet each other in a gear is called the Gear Mesh Frequency (GMF), f_m (Hz) [45].

$$f_m = N \times f_r \quad (3.2)$$

where N is the number of teeth on the gear and f_r is shaft rotational frequency (Hz). However, for the planetary gears, the gear mesh calculation is more complex and it can be obtained using Table 3.3 [46] below.

3.7 Gear life prediction

Loads, operating temperature, lubrication quality and alignment that have an important role in the operational life-time of gears in gearbox.

Both British Standards and International Standard organization have developed theoretical methods for estimating gear wear and fatigue [47]. However, these theoretical

Table 3.3: Planetary gear frequencies, the acronyms used in the equations are listed in Table 3.4

Frequency name	Equation
Rotational speed of career	$S_c = \frac{S_s}{(1 + \frac{N_r}{N_s})} = \frac{S_s}{(2 + \frac{2N_p}{N_s})}$
Rotational speed of planet gears	$S_p = S_c(1 - \frac{N_r}{N_p})$
Rotations of number of teeth	$N_r = N_s + 2N_p$
Fundamental gearmesh frequency	$F_{mesh} = N_s(S_s - S_c) = N_p(S_p - S_c) = N_r S_c$
Gear mesh frequency (GMF)	$GMF = n_p F_{mesh} = n_p N_r S_c$
Sun gear defect frequency	$F_{sun} = n_p(S_s - S_c)$
Planetary gear defect frequency	$F_{planet} = 2S_c(1 - \frac{N_r}{N_p})$
Ring gear defect frequency	$F_{ring} = n_p S_c = \frac{n_p S_s}{(2 + \frac{2N_p}{N_s})} = \frac{n_p S_s}{1 + \frac{N_r}{N_s}}$

Table 3.4: Description of the symbols used in Table 3.3

	Symbol	Description
Sun gear	S_s	Sun rotational gear speed
	N_s	Number of teeth on sun gear
	F_{sun}	Sun gear defect frequency
Planet gear	S_p	Planet gear speed
	N_p	Number of teeth on planet gear
	F_{planet}	Planet gear defect frequency
	n_p	Number of planet gears
Ring	N_r	Number of teeth on ring gear
	F_r	Ring gear defect frequency

calculations fall short of what actually happens in the field. This is due to the loading conditions as well as inconsistencies in lubrication quality, resulting in accelerated wear and fatigue.

3.8 Wind turbine drive train architecture

Figure 3.8 shows the general architecture of the turbine drive-train. As it can be seen trunnion mounts are used on both sides of the gearbox to stick it to the bed plate. An elastomeric bushing is normally used to reduce the noise and vibration [48].

3.9 Modular structure of gearbox in turbines

Typically, a gearbox is composed of two or three stages either planetary or parallel stages to be able to increase the speed. Gears are encapsulated within the gearbox housing. Torque arms are included in the gearbox housing to decrease the extra torque. A lubrication system is included to provide lubrication to the rotating components. Sensors are used to monitor important operational parameters of the gearbox including rotational speed, oil temperature, vibration levels, etc. Figure 3.9 shows a general schematic diagram of a typical three-stage gearbox [48, 50].

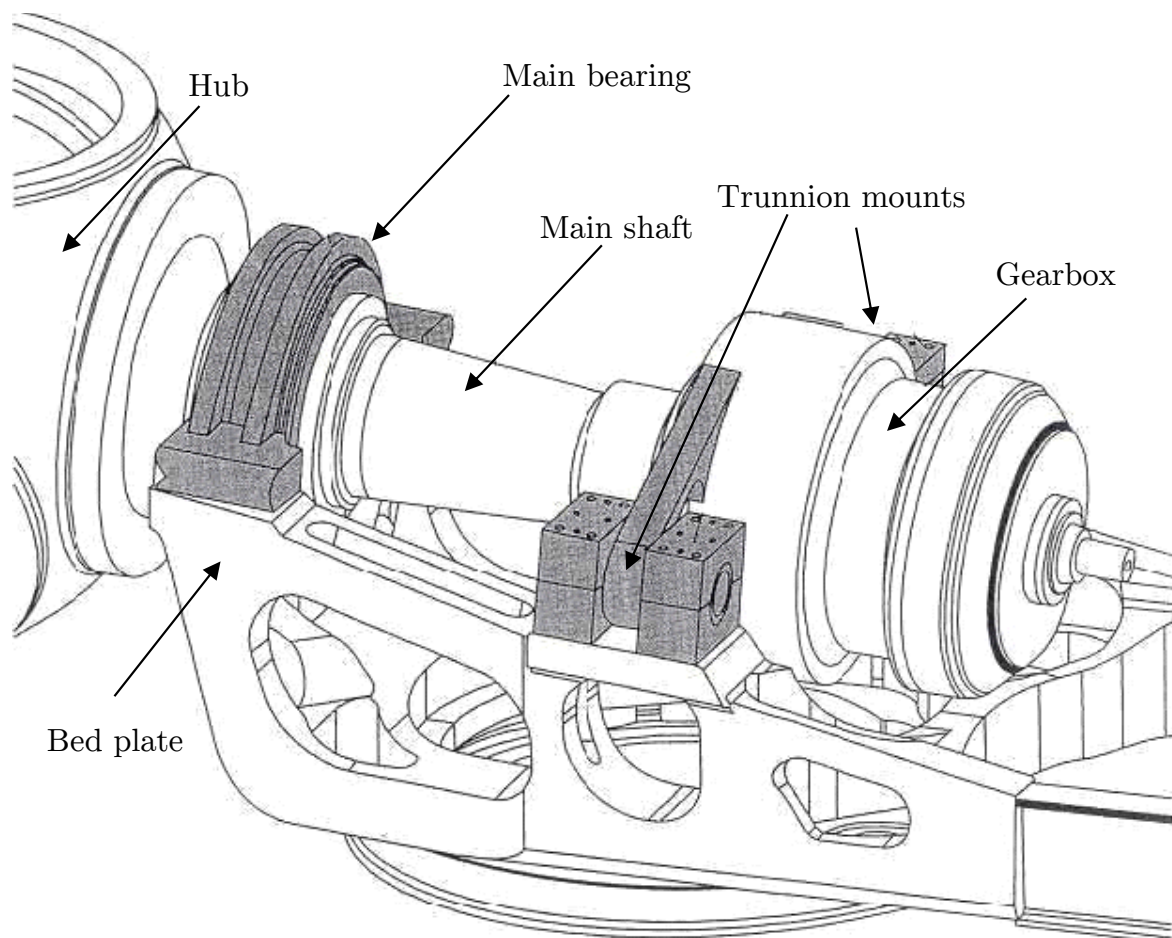


Figure 3.8: General structure of turbine drive train [49].

The low speed stage of the gearbox has a planetary shape using both helical and spur gears. The next stage is the parallel intermediate shaft consisting of helical gears driven by the sun pinions. The high speed stage also uses helical gears and is rotated by the intermediate shaft [48].

The planetary stage gears depend on the torque to be transmitted. Therefore different designs for planetary stage of the gearbox exist. In simple planetary, each planet shaft carries one planet gear whilst in compound planetary, one planet shaft carries two planet gears. The types of the gears usually used in these stages are helical and spur gears [50]. Planetary gears are used in first stage of wind and tidal turbines. However, planetary gears are more complex in comparison with parallel shaft gears. Annulus deformation and deflection in planet gears could affect the planetary gears causing them to develop damage earlier than anticipated by the design [48].

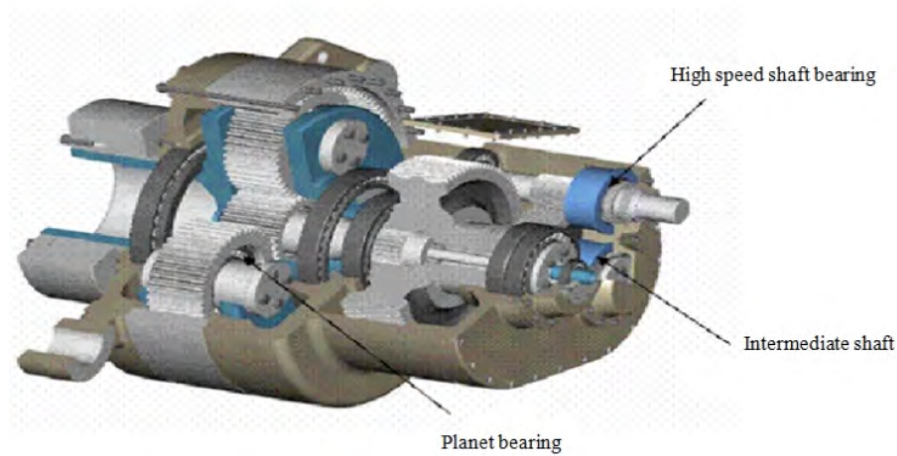


Figure 3.9: General view of three stage gearbox [51].

Figure 3.10 shows more details of a three-stage gearbox. The critical bearing locations have been defined in Figure 3.10. It can be seen that there are three types of bearings including, the planetary bearing, intermediate shaft bearing and high-speed bearings [48].

Figure 3.11 shows the modular definition of large scale gearbox.

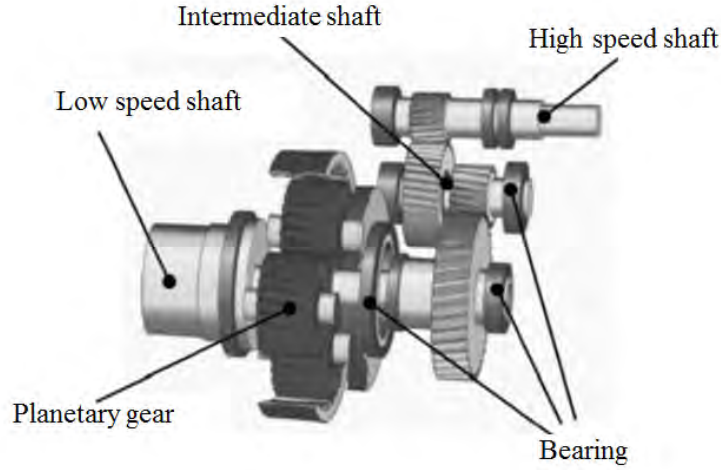


Figure 3.10: Another view of three stage gearbox [52].

3.9.1 Gear mesh characteristics

As the gearbox transmission system in wind and tidal turbine is a periodic system, its spectrum contains components at gear mesh frequencies and their harmonics as well as shaft frequencies and their harmonics. As described in Section 3.6 the fundamental GMF is the number of the gear teeth multiplied by the shaft rotational frequency.

The appearance of the GMF in the spectrum is related to the rotational speed of the gearbox. When the gearbox holds a steady speed, GMF would appear together with their harmonics in the frequency spectrum. If the gearbox changes speed, either due to acceleration or deceleration, GMFs are observed as transients in the spectrum.

The amplitude of the GMF component is heavily affected by the force of which it is transmitted from the involved gears. Any modulation will have noticeable effect on the observed amplitude of GMF in the spectrum [53].

3.9.2 Bearing characteristic frequencies

Bearing defects give rise to specific frequencies which are known as fundamental defect frequencies of the bearing. Finding these fundamental defect frequencies is very impor-

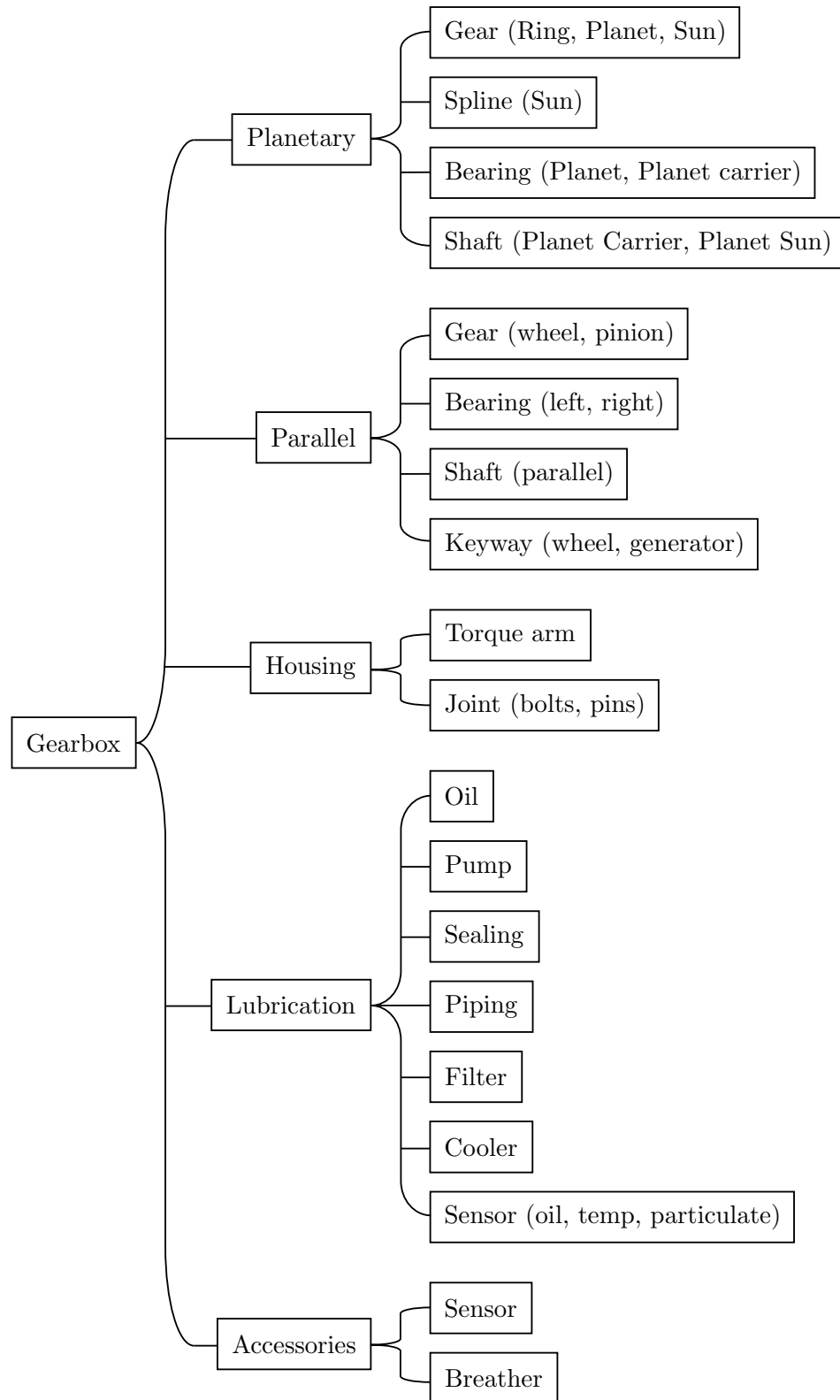


Figure 3.11: Modular definition for gearbox of the turbine [50].

tant in identifying any possible bearing faults. When a defective bearing rotates, any irregularity in rolling element of the bearing or raceway surface, as shown in Figure 3.12, will excite one or more of these fundamental frequencies [54]. The amplitude of these frequencies will point out the condition and the severity of the bearing defects. If the shaft speed and the type of the bearing are known then it would be possible to calculate the defect frequencies. However, these frequencies are usually provided by the manufacturer of the bearing.

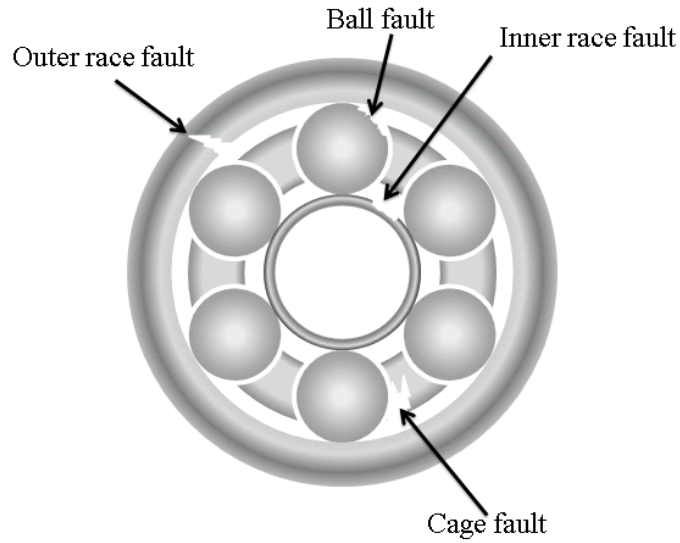


Figure 3.12: Schematic of different bearing defect [54].

Table 3.5 shows four characteristic fault frequencies for bearing where N is the number of balls, F is shaft frequency (Hz), B presents Ball diameter (mm), P is pitch diameter (mm) and θ represents contact angle.

3.10 Materials for structural components

There are wide varieties of materials that can be used to make gears but the most common type of material for wind and tidal turbine gears is high chromium steel [55].

Table 3.6 shows the percentage of materials used in current industrial turbines considering that nacelle is $\frac{1}{3}$ gearbox and $\frac{1}{3}$ frame and machinery parts. Also rotor blades are

Table 3.5: Bearing fundamental frequencies formula [54]

Name	Formula
Ball Pass Frequency Inner Race	$BPFI = \frac{N}{2} \times F \times (1 + \frac{B}{P} \times \cos(\theta))$
Ball Pass Frequency Outer Race	$BPFO = \frac{N}{2} \times F \times (1 - \frac{B}{P} \times \cos(\theta))$
Fundamental Train Frequency	$FTF = \frac{F}{2} \times (1 - \frac{B}{P} \times \cos(\theta))$
Ball Spin Frequency	$BSF = \frac{P}{2B} \times [1 - (\frac{B}{P} \times \cos(\theta))^2]$

made from both wood epoxy, glass reinforced plastic or injection moulded plastic with carbon fibres [56].

Table 3.6: Percentage of materials used in large and (small) turbines [56]

Components	Permanent magnet materials	Pre-stressed concrete	Steel	Aluminium	Copper	Glass reinforced plastic	Wood epoxy	Carbon filament reinforced plastic
Hub			(95)-100	(5)				
Blade			5			95	(95)	(95)
Nacelle	(17)		(65)-80	3-4	14	1-(2)		
Gearbox			98-(100)	(0)-2	(<1)-2			
Generator	(50)		(20)-65		(30)-35			
Frame, Machinery and shell			85-(74)	9-(50)	(4)-12	3-(5)		
Tower		2	98	(2)				

3.11 Gearbox damage mechanism, faults and maintenance

According to a number of recent studies [57,58] all subsystems of wind and tidal turbines, including rotor, blades, pitch control system, yaw system, drive-train, generator and power electronics, gearbox faults are the most commonly occurring.

Gearbox failures can be attributed to various root causes in damaged gear, bearings and/or lubrication [59].

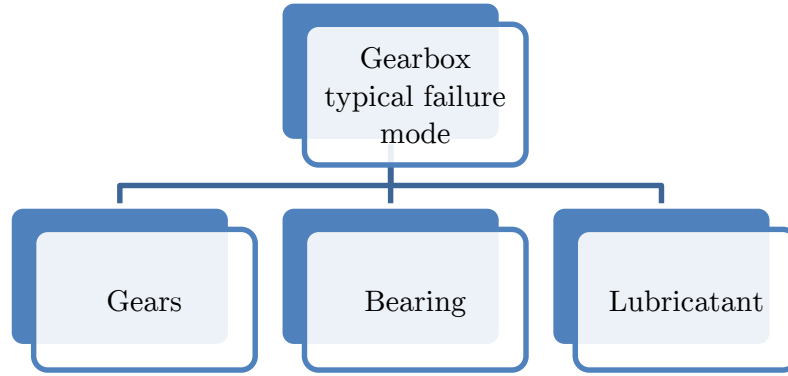


Figure 3.13: Typical causes of gearbox failures [59].

In this section, different aspects of gearbox failure are considered in detail.

According to McNiff [60] bearing defects are the leading factor of gearbox failure in wind turbines. Certain studies have indicated that about 10% of all gearbox defects could be related to manufacturing quality issues or gear-related anomalies. However this has not been found not be the main cause of failures although it does need to be taken into account [48].

Sheng [59] shows that from the data of 257 defective gearboxes considered in his study, 70% were attributed to bearing defects, 26% to gear defects and 4% to other types of defects. illustrates the different gearbox failure modes based on NREL's findings [59].

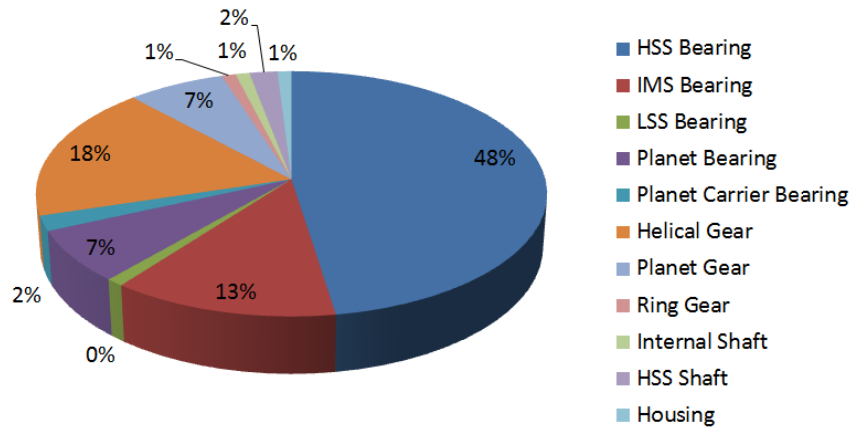


Figure 3.14: NREL Failure of bearing, shaft and gears of gearbox reproduced from [59]

Figure 3.15 shows the most common failure modes of wind turbines divided into two main categories, catastrophic failures and non-catastrophic failures [59].

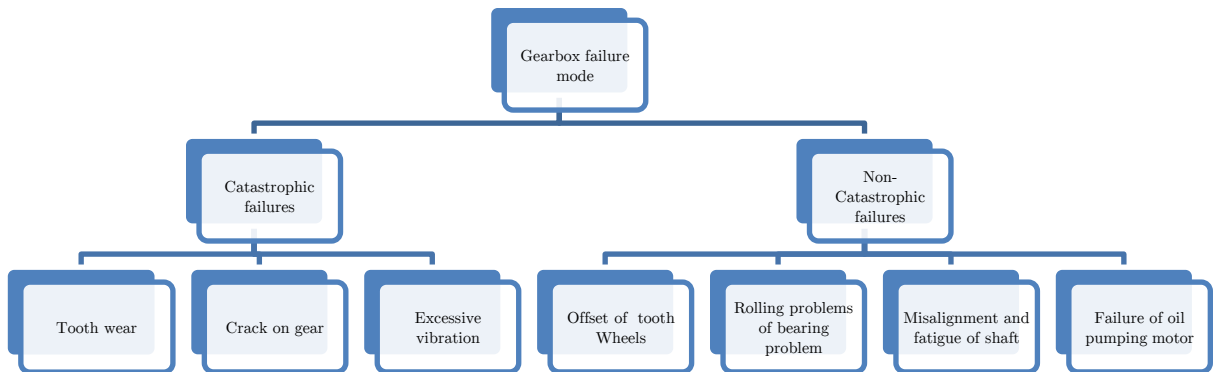


Figure 3.15: Block-diagram of most common failure modes of wind and tidal turbines.

There are several reasons that can lead to gear failure, e.g. scoring, wear, pitting, fatigue, impact, plastic deformation, tooth fracture due to overloading, etc. Figure 3.16 shows different modes of gear failure in depth. Fatigue is one of the most common root causes of gear failure. Tooth bending fatigue and surface contact fatigue are the most common fatigue failure modes in gears. Poor gear design, misalignment or incorrect assembly and overload can accelerate fatigue failure [48].

Certain gear defects are more severe in nature in comparison with others, because once

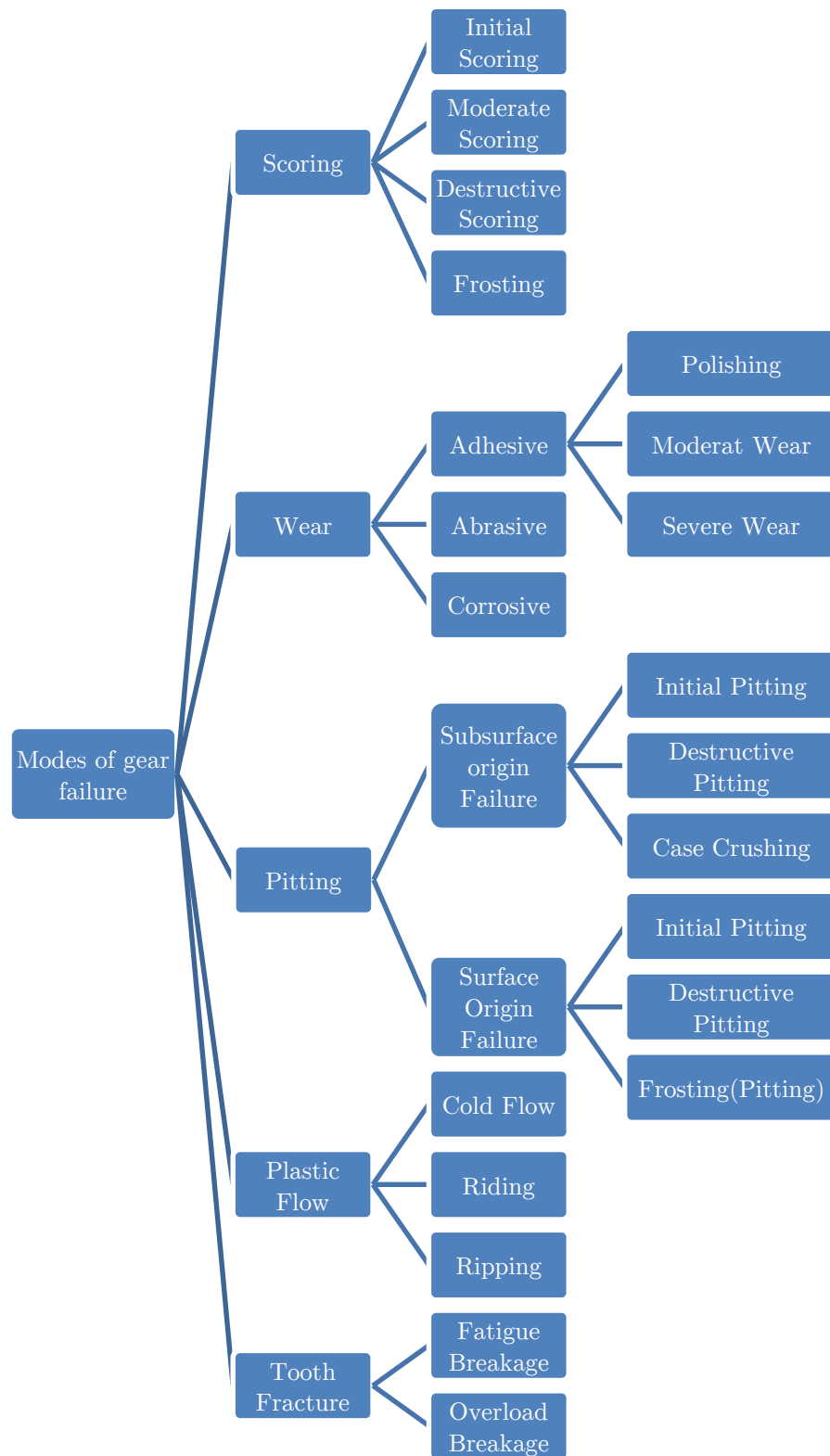


Figure 3.16: Different gear failure modes [64].

the initiate they will grow rapidly. From these defects, tooth breakage, scoring, pitting and lubrication are of most interest [53,61–63]. Gear defects result in an increase in the noise and vibration level of the system.

Tooth breakage

One of the most severe gear defects is tooth breakage. This type of defect can eventually lead to failure of other gearbox components, such as bearings and shafts. Figure 3.17 shows an example of tooth breakage caused by bending fatigue [65].



Figure 3.17: Gear tooth breakage [66].

Scoring

Scoring is the result of two separate root causes:

- 1) Lubrication failure in the contact region.
- 2) Accelerated metallic contact surface due to welding and abrasive action despite applied load, speed and oil temperature remaining constant.

Usually scoring occurs predominantly in the pitch line area as the lubrication is very low at this region [64]

There are three types of scoring, initial, moderate and destructive [64].

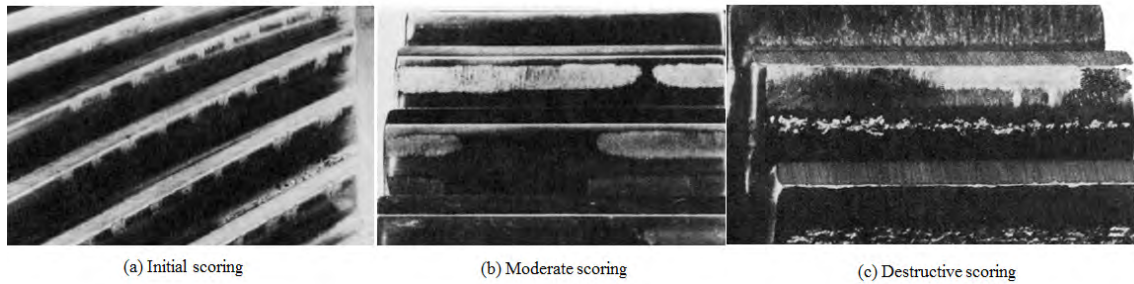


Figure 3.18: Different types of gear scoring (a) Initial scoring (b) Moderate scoring (c) Destructive scoring [64].

Wear

Gear tooth wear occurs when layers of the metal are removed from the surface due to frictional and contact forces. Over a long period of time noticeable wear will happen which can be aggravated further by poor lubrication [64].

Wear nature can be classified into three categories [64]:

- 1) Adhesive

- 1-1) Polishing

- 1-2) Moderate wear

- 1-3) Severe wear

- 2) Abrasive

- 2-1) Mild abrasion

- 2-2) Severe abrasion

- 3) Corrosive wear or chemical wear

Also there are three main factors leading to gear tooth wear [64]:

- 1) Dry metal to metal surface contact due to lack of oil film

- 2) Presence of hard abrasive particles in the oil

- 3) Chemical wear because arising from the composition of oil used and additives present

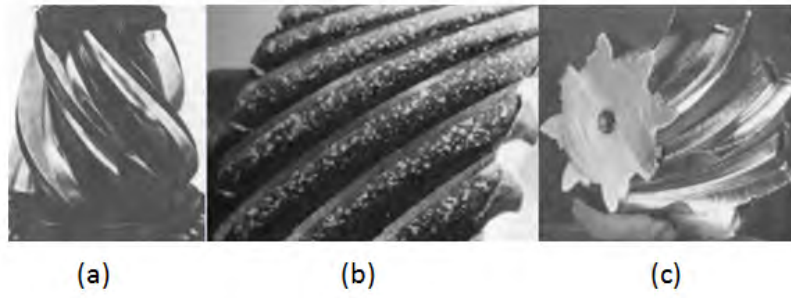


Figure 3.19: Adhesive wear: (a) Polishing wear, (b) Moderate wear [64].

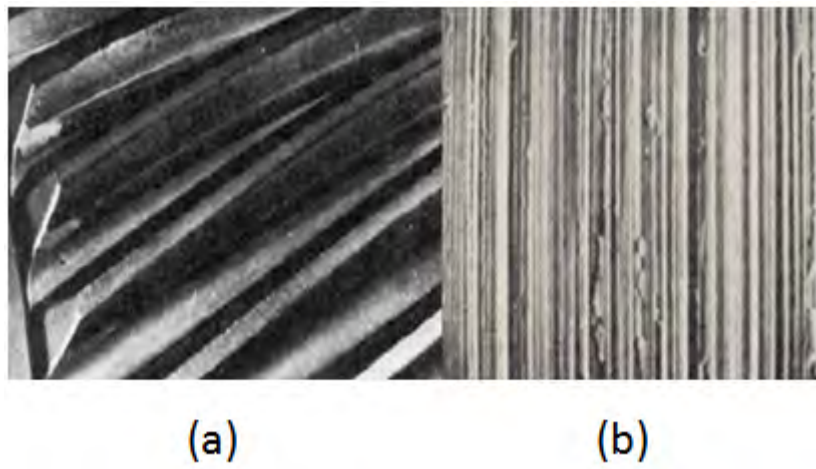


Figure 3.20: Abrasive wear: (a) Mild abrasion, (b) Severe abrasion [64].



Figure 3.21: Corrosive wear or chemical wear [64].

Fatigue Pitting

Pitting is the result of cyclic loading conditions on the surface of the gear tooth causing bits to break off with time due to micro-cracks evolving. Pitting will spread very rapidly as the un-pitted gear tooth areas have to sustain the load which carried out by the damaged gear tooth previously. Following this, pitting will increase load effects and causing fracture of the weakened gear tooth [64].

There are two main types of pitting:

1) Subsurface pitting

1-1) Initial pitting

1-2) Destructive pitting

1-3) Case crushing

Surface-initiating failure

2-1) Initial pitting

2-2) Destructive pitting

2-3) Frosting

Figure 3.22 shows an example of gear tooth pitting [64].



Figure 3.22: Gear tooth pitting [67].

Plastic flow

High contact stresses will cause yielding of in the tooth causing plastic flow. Fig 3.23 presents an example of failure due to plastic failure [39,68].



Figure 3.23: An example of plastic flow defect [69].

Bearing failure

Bearings along with gears are critical structural components of any gearbox. Bearings are divided into two main groups, roller bearing and ball bearings. Both have similar mechanical mechanisms [4]. Roller bearings consist of rollers, inner and outer races [4]. Bearing failure will cause the gearbox to fail as well potentially with catastrophic consequences. Bearing failure mechanisms are similar to those discussed earlier for gears [70]. A number of studies have indicated that almost two thirds of all gearbox failures are the result of bearing failures [71]. There are several bearings in wind turbine gearboxes. Regarding to the location of the bearing and considering if it is high speed shaft (HSS), intermediate speed shaft (IMS), low speed shaft (LSS) or planetary, bearing failure can be categorised accordingly [71]. As shown in Figure 3.24, the high-speed shaft bearing has the highest failure rate. Poor lubrication, poor maintenance, misalignment, excessive rotational speed or frequent speed variations, imbalance and inappropriate environmental conditions such as humidity and dust can be responsible for bearing failure [72].

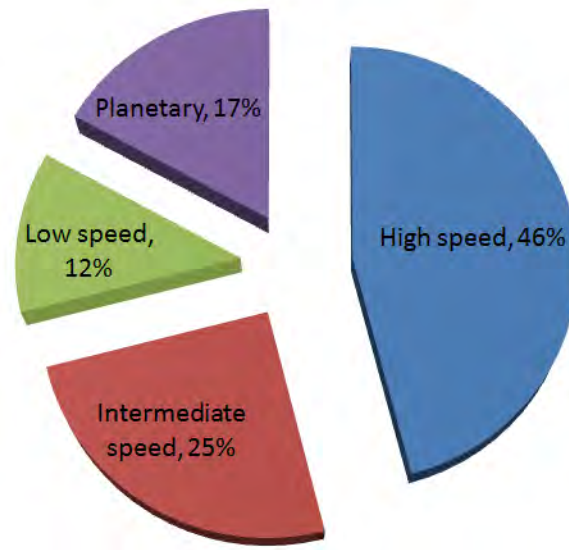


Figure 3.24: Bearing failure in gearbox regarding to their location [71].

Common defects in rolling bearings can be classified into damaged rollers normally caused due to misalignment, broken cage, skidding, spalling on the outer race and smearing associated with discolouration of metal and normally arising from poor lubrication [73].

Figure 3.25 shows that friction and wear-related bearing defects will result in, pitting, seizure, flaking, brinelling, fluting and spalling producing additional noise in the form of acoustic ultrasonic and audible waves [72].

Lubrication failure

Lack of lubrication can result in catastrophic failure, increasing down-time of wind and tidal turbines. Having efficient lubrication will increase considerably the lifetime of critical components.

The lubricant film is needed to prevent the dry contact between the rolling elements of bearing. Inefficient lubrication causes metal to metal contact and overheating of bearings. Discolouration of roller elements, rings and cages is a symptom arising from poor lubrication. Also, high operational temperature can cause lubrication failures due to the lubricant breaking down or changes in the viscosity. Above the flashpoint of the lubricant

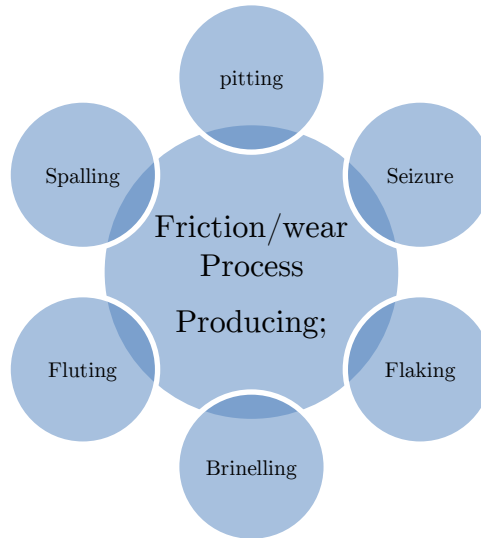


Figure 3.25: Source of acoustic emission in bearing

combustion will occur, possibly leading to the loss of the turbine. In wind turbines some bearings work at low speed which causes wear due to inefficient lubrication [70].

The block diagram presented in Figure 3.26 summarise the most common failure modes of wind and tidal turbine gearbox.

3.12 Summary

In this chapter, different types of turbines categorised based on their generator technology, were studied and significant of the gearbox in the turbines were discussed. Gearbox damage mechanism and its modular structure were also reviewed.

The next chapter will focus on the techniques and tools available to detect the degradation and damages in the wind and tidal turbines, in particular the gearbox used in the drive train.

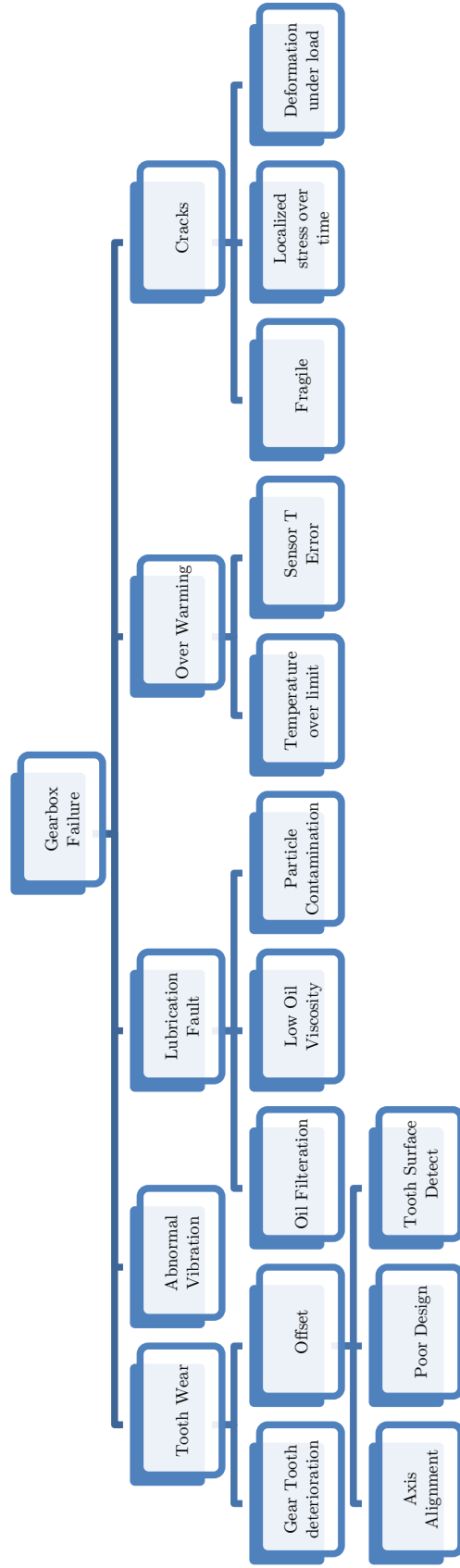


Figure 3.26: Common gearbox failures.

“Science is magic that works!”

— *Kurt Vonnegut*

Chapter 4

Condition monitoring and signal processing techniques

4.1 Introduction

In the previous chapter, different types of turbines and various fault mechanism in the turbines, were explored. In particular, the gear box of turbine is prone to degradation and damage. In this chapter the condition monitoring techniques that are commonly employed to assess the health of gearbox in wind turbines are discussed.

Wind turbine maintenance has been originally based on reactive and preventive maintenance. This means that corrective approaches are employed to restore wind turbine operation after failure occurs and preventive maintenance is carried out to replace components that may fail catastrophically based on empirical data [57, 74, 75]. However, due to the increasing wind and tidal turbine size as well as the location of offshore wind farms preventive and predictive maintenance has become necessary. Fault diagnosis techniques and condition monitoring help condition based and predictive maintenance strategies to become more applicable [76]. A Condition Monitoring System (CMS) includes appropriate sensors providing useful data that can be analysed at regular time intervals by implementation of different signal processing methods to define the health status of the different

components of wind and tidal turbines including the drive-train. Therefore, faults can be diagnosed or prognosed and the exact requirement of maintenance can be planned helping prevent further damage of critical components [77]. The objective of CM and maintenance of wind and tidal turbines is to ensure reliability, deploy the minimum resources required and recover from unexpected breakdowns as quickly as possible [78].

It has been shown that the cost of O&M for turbines is about 20-25% of the total Levelised Cost of Electricity (LCOE) [74, 75]. Therefore, defect diagnosis and condition monitoring of wind and tidal turbines has great benefit to offer for large-scale wind and tidal turbines in reducing O&M.

There are numerous condition monitoring techniques such as vibration, acoustic emission, ultrasound test, oil analysis, strain measurement, and temperature measurement coupled with different signal processing methods which are able to provide continuous useful data regarding the health status of different subsystems of wind and tidal turbines, including tower, generator, bearing, gearbox and blades [79, 80]. The importance of the condition monitoring of wind and tidal turbines are confirmed in many studies carried out on wind and tidal turbines [58, 74, 81–83].

Condition based maintenance will decrease the risk of total loss of industrial large scale wind turbine due to catastrophic failure by enabling timely maintenance to take place based on the evaluation of the actual condition of wind and tidal turbines [84]. To evaluate the health condition of the wind and tidal turbine drive-train, the main bearing, main shaft, gearbox and generator bearing should be monitored.

Condition monitoring can be carried out remotely with data collected at regular time intervals by automated measurement systems. Continuous condition monitoring can provide instantaneous feedback of condition but data generated may be excessive depending on the component being evaluated [85]. An overview of different algorithms which are developed to monitor specifically for gearbox is presented in the next section. An overview of different algorithms which are developed to monitor specifically for generator is presented in the next section.

4.2 Common condition monitoring techniques

4.2.1 Vibration analysis

Vibration is related to the movement back and forth or up and down of a structure or system. Figure 4.1 shows the causes of machine vibration [86].

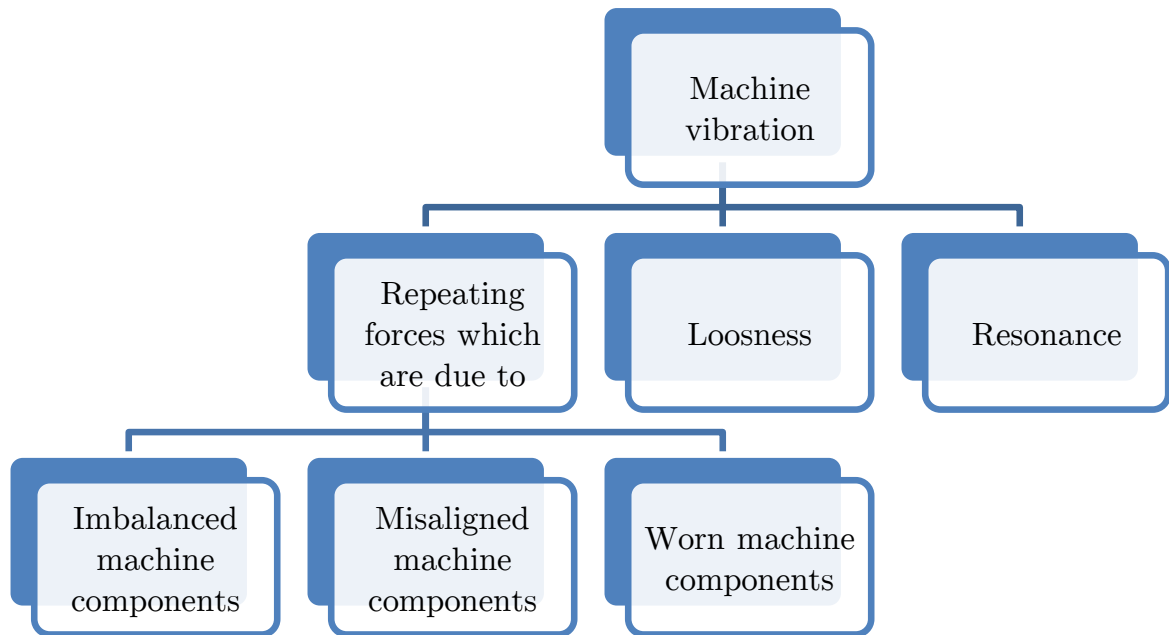


Figure 4.1: Causes of machine vibration.

Almost all mechanical equipment has some sort of natural vibration and gearboxes used in wind and tidal turbines are not exempt of that. This suggests that if some part of the mechanical equipment is not functioning as it should, it will affect their natural vibration. Indeed, it is possible to detect the defect in gearbox by observing the change in their vibration.

Different kinds of wind and tidal turbine rotating machinery faults usually will raise the vibration level of the turbine. This vibration can be recorded with accelerometers and converted into electrical signals for data analysis [87].

Vibration analysis is the most popular technique for evaluating the condition of rotat-

ing machines, e.g. gearbox and bearing in wind and tidal turbine as it can diagnose about 60% of machine defects [58]. For different frequency ranges, different sensors are required. Proximity transducers are used for low frequency ranges whilst velocity sensors are used for middle range of frequency. Vibrations in the high frequency range are recorded using accelerometers [88]. Vibration analysis is performed online and data analysis can be automated [89,90]. According to [91] Ismail and Marshal the amplitude of the vibration signal can indicate the magnitude of the applied forces. Vibration signals can be affected by the dimensions of the gears as well as gear eccentricity, tooth stiffness, errors in profiles and pitch.

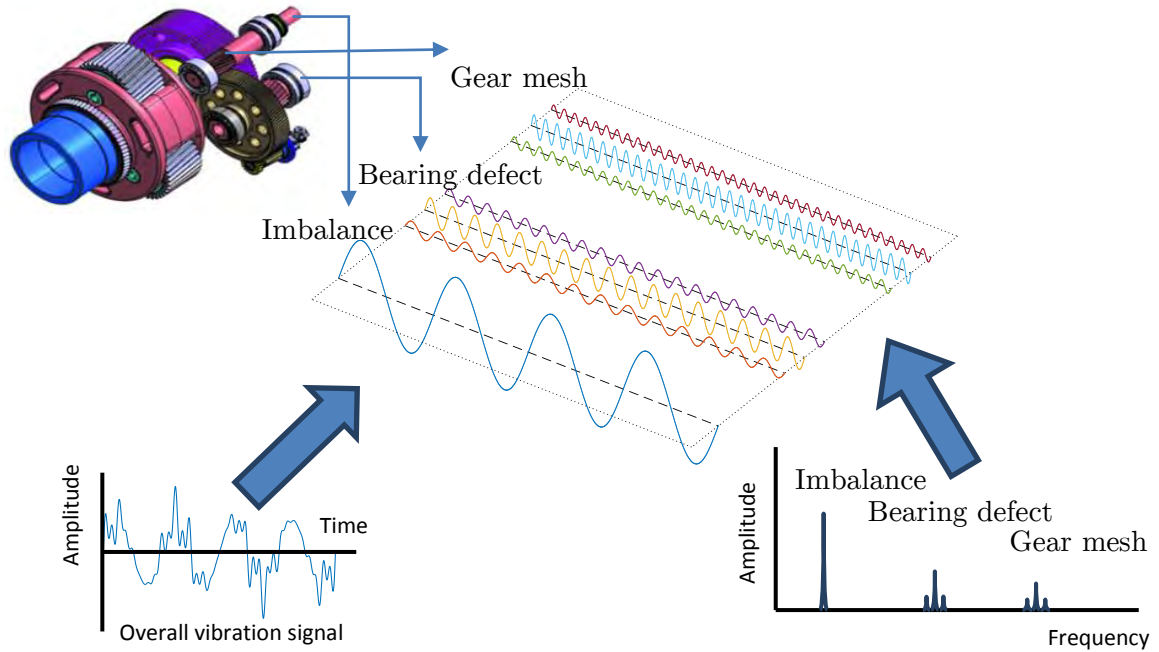


Figure 4.2: Vibration analysis of gearbox [92].

Figure 4.2 shows that in a gearbox as the gear teeth rotate and vibrate, the vibration signal will be transmitted through the shaft and bearing, reaching the gear housing where the accelerometer has been installed for vibration data collection. As the vibration signal travels through this path, it will attenuate and other vibration signals from other drive-train components, like bearing and shaft will add to it. It can be seen that the overall

vibration signal in time domain is not very informative. Therefore, to obtain the desired information, further signal processing and filtering would be required.

Vibration signal analysis is convenient for condition monitoring of wind and tidal turbine gearbox as observing any changes in vibration signals could reflect a change in gearbox condition. Any fault on gears would cause amplitude modulation and phase modulation in vibration signal of the gearbox. Therefore, any small changes in the vibration signal can be processed to indicate the possible defect of wind and tidal turbine gearbox [93,94].

In general vibration signals in gearbox of wind and tidal turbine made from three main components which have been shown in Figure 4.3 [53].

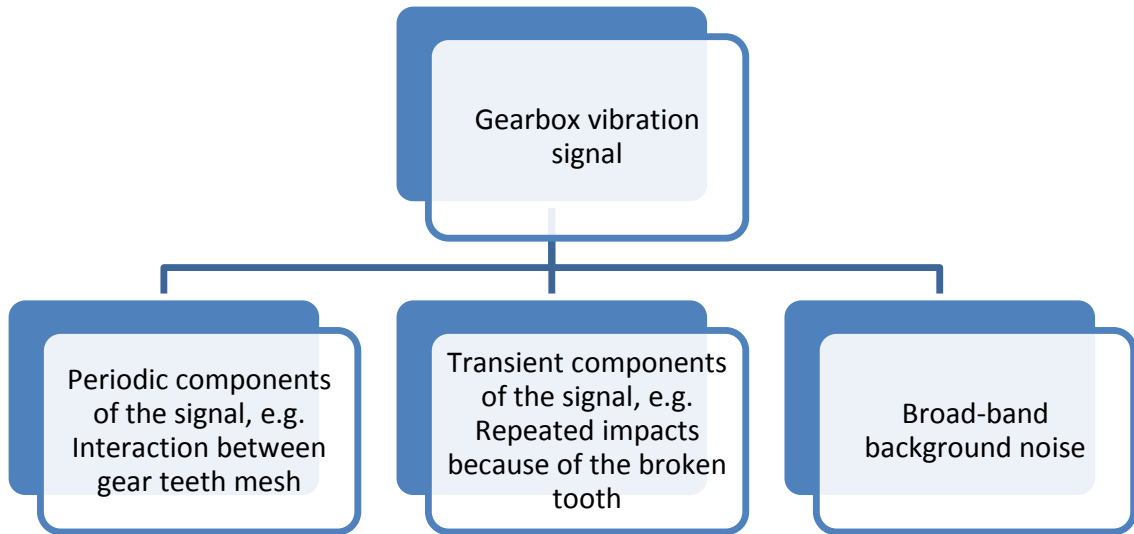


Figure 4.3: Three main components of wind and tidal turbine vibration signal [53].

4.2.2 Acoustic emission analysis technique

Acoustic emission is a non-destructive testing (NDT) method which can be employed in order to detect and locate defects on rotating machinery system and components. When a component is under stress a flaw or crack initiating and propagating will result in the emission of energy in the form high frequency stress waves causing oscillations on the surface of the component. Piezoelectric sensors which are located on the loaded

component detect these oscillations and convert it to an electric signal or voltage. An amplifier is used to further amplify the weak piezoelectric signal, before it is digitally acquired and analysed. Analysis of the collected signal data permits its characterisation and relation of the signal features of interest to a particular defect [95]. For example, when the outer race of the bearing has developed a surface defect, the surface of roller balls will interact with the work surface of the outer race producing impact noises in the form of acoustic emission signals which can be detected, digitised and subsequently analysed [72].

The fundamental principles of acoustic emission testing are shown in Figure 4.4

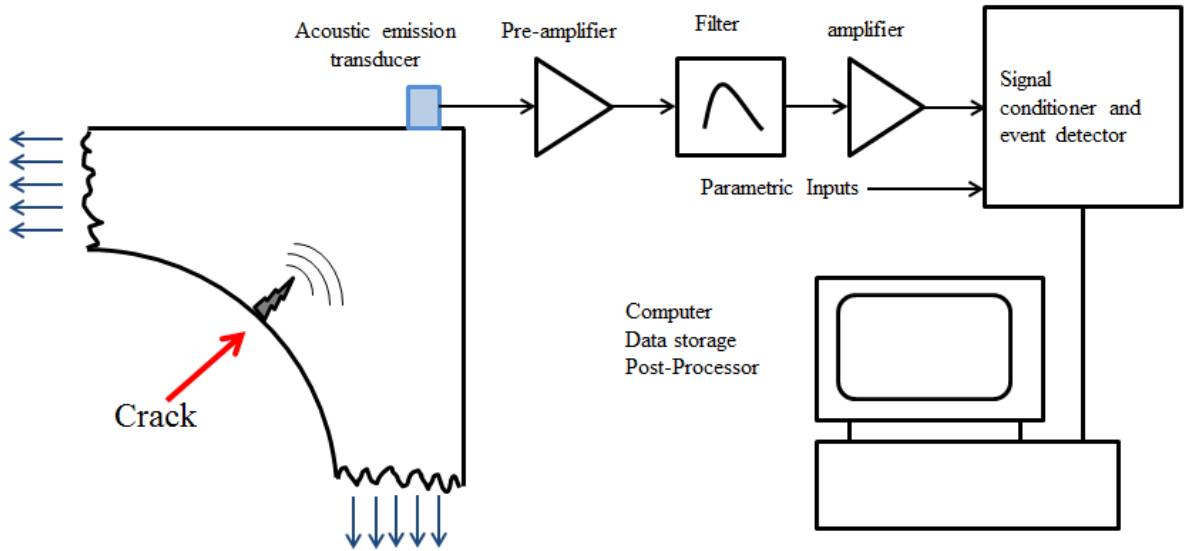


Figure 4.4: Process of acoustic emission test [96].

When the AE sensor detects the signal over a certain threshold which has been produced from the crack, an AE event has occurred. Since AE signals are weak, an amplifier is connected to the AE sensor to increase the signal gain. To remove the noise, the signal is passed through a filter. At the end the AE features are subtracted and then saved in a computer for further analysis [96].

The acoustic emission sensor uses a piezoelectric element which converts the elastic energy of a propagating surface wave into electric signals through the direct piezoelectric effect [4].

The schematic diagram of the acoustic emission sensor is shown in Figure 4.5. It can be seen that the sensor contains a thin piezoelectric disk with electrodes connected to it [4]. The AE sensor is attached to the testing surface by using magnetic hold-down or mechanical clamp and is coupled using grease or other suitable couplant [97].

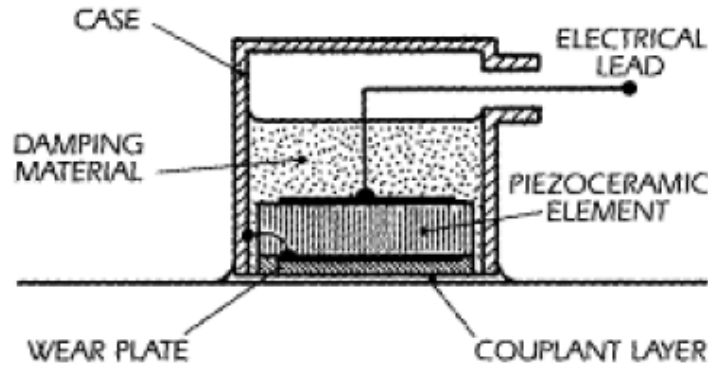


Figure 4.5: Typical acoustic emission sensor [98].

The main problem of the acoustic emission test technique is the attenuation of the signal and because of that the acoustic emission sensor should be as close as possible to its source [72]. The most measured acoustic emission parameters to detect the defect would be amplitude, root mean square (R.M.S), energy, kurtosis and crest factor which will be discussed in depth in Chapter 4 [99].

Comparing acoustic emission and vibration analysis shows that acoustic emission offers the earlier failure detection as its sensor is much more sensitive [72].

4.2.3 Supervisory control and data acquisition

The Supervisory Control and Data Acquisition (SCADA) unit is a real-time software which is used to control the hardware and also acquiring the data into a computer system. SCADA is a central control system which consists of a control network interface, input and output, communication equipment and software. SCADA systems are used to monitor and control the equipment in various industrial processes, including manufacturing, production, development and fabrication.

The SCADA system is a centralised system that monitors and controls the entire area. A supervisory system gathers data from the field and transmits them to the dispatch centre. The SCADA can also transmit control commands to the field from the dispatch centre so operation is interactive. The SCADA is normally a Remote Terminal Unit (RTU) or Remote-Control Centre (RCC). Several control actions can be performed automatically by RTUs without human intervention being required.

4.2.4 Other common condition monitoring techniques

Ultrasound testing technique

This technique is used widely by the wind energy industry to examine the structure of tower and blades of the turbine. Generally, the ultrasound testing technique is employed to detect and quantify subsurface defects. The reflections of the interrogating ultrasonic waves can provide an estimation of the location, geometry and size of the defect. Also signal processing such as wavelet transform or time-frequency techniques can be used to extract more information [100–102].

Oil analysis

It has been shown that oil debris monitoring is a viable condition monitoring method for early detection and tracking of damaged gear and bearing elements in the wind turbine drive-train [87]. To define the condition of various moving components, most of the time, oil analysis is carried out. Although there are online sensors to monitor oil temperature, moisture and contamination, oil analysis is conventionally carried out by taking samples during a planned outage [58, 103]. While defects are developing small vibration might be evident but analysing the oil samples will provide useful information which can provide early warning [104]. The advantages of oil analysis is that it is efficient and cost effective and prevents catastrophic failure [105, 106].

Strain measurment

This technique is used to protect blades against high stress levels and lifetime forecasting by using stain gauges. Strain gauge sensors are installed on blades [107]. Optical fibre sensors based on Fibre Bragg Gratings (FBGs) can be used in the place of conventional strain gauges but they are far more expensive [58].

Temperature measurment

Passive thermography is often used for electronic and electric components to identify overheating [108]. Active thermography can be employed to assess the structural integrity of the blades. Thermographic inspection is applied offline [109–111].

4.3 Signal processing techniques

In general, the signal processing techniques can be divided into three main categories depending on the signal domain. The first two groups are time and frequency domain analysis and the third group is a mixture of these two domains. These groups will be discussed in more details next.

4.3.1 Time domain analysis

Time-domain of analysis is reasonably simple, yet very effective to diagnose problems in the system. Some of the most common algorithms employed are explained here.

Peak to Peak Value

The peak value is the maximum path of the signal from zero or its imbalance point. Therefore, the peak to peak value (Pk-Pk) is the length from positive peak to negative peak. In the case of symmetrical signal the Pk-Pk value is twice the peak value but not necessarily for all signals shapes [45, 112].

Root Mean Square

RMS value is another measure of the power level or energy level of the signal and can be calculated by using equation 4.1 within the specific window length, t .

$$V_{rms} = \sqrt{\frac{1}{t} \times \sum_{i=1}^t x_i^2} \quad (4.1)$$

From the other point of view it can be say that RMS is the normalised value of standard deviation of the signal [112] and can be shown as equation 4.2.

$$V_{rms} = \sqrt{\frac{0}{t} \sum_{i=1}^t (x(i) - \bar{x})^2} \quad (4.2)$$

Where, $\bar{x}$ is the mean value of the signal and it can be calculated from equation 4.3

$$\bar{x} = \frac{1}{t} \sum_{i=1}^t x(i) \quad (4.3)$$

Although in time domain analysis, calculating the overall RMS level of the rotating machine vibration signal is considered as the simplest of the algorithms typically used for analysis, it is not good enough to detect defects at very early stage and does not provide any information of which component might be damaged since it does not offer any rotational information [113]. The use moving RMS can increase sensitivity.

RMS is one of the measures of the overall vibration level of the system. RMS becomes more useful when tooth damage grows. RMS has been considered as an appropriate algorithm for monitoring the overall behaviour of the gearbox but it is sensitive to operational conditions like speed and load which can affect its usefulness in a wind or tidal turbine environment [114].

Crest Factor

Crest factor (CF) or “Peak-to-RMS-ratio” is the ratio of the peak amplitude value of the signal to the RMS value of the signal with no units [112]

$$CF = \frac{Peak}{RMS} \quad (4.4)$$

Crest factor is a technique which is measuring the smoothness of a signal, in other word Crest factor technique will be used to determine the amount of impact occurred in the signal. Sharp impacts on signal could be because of gear tooth wear defect, cavitation or roller bearing wear [115].

Ingarashi et al. [116] stated that for the healthy bearing signal the approximate value of the crest factor is 5 The RMS value increases as the defect propagates in bearing therefore the crest factor will decrease [117].

Kurtosis and Skewness

The kurtosis and skewness are two statistical measures that together give a good indication about the shape of signal. In the other word they describe the distribution and location of the data. These measures can be very useful in detecting the defect from the time domain signal and the shape of induced peaks in the signal.

Kurtosis is a measure that indicates the amount of spikiness and flatness of the signal and is known as the fourth moment of standard deviation [118] and is calculated by

$$Kurtosis = \frac{\sum_{i=1}^N (x_i - \bar{x})^4 / N}{\sigma^4} \quad (4.5)$$

where $\bar{x}$ the mean and σ is the standard deviation. This equation will produce a value of 3 for a standard normal distribution, thus, frequently it might be seen that people define the above equation with a “-3” at the end, so the result of the equation will be 0 for the reference curve of normal distribution. The latter is also known as excess kurtosis.

There are several definitions to calculate the skewness, however a simple definition is known as Pearson Mode Skewness [119] is defined as

$$Skewness = \frac{\bar{x} - mode(x)}{\sigma} \quad (4.6)$$

where $\bar{x}$ is the mean and σ is the standard deviation.

Figure 4.6 shows the value of kurtosis calculated on two different signals taken from two wind turbine. The signal on the left is from a healthy turbine and as it can be seen the value of kurtosis remains around 3 while on the right the value of kurtosis goes as high as 45 which indicates a damaged wind turbine.

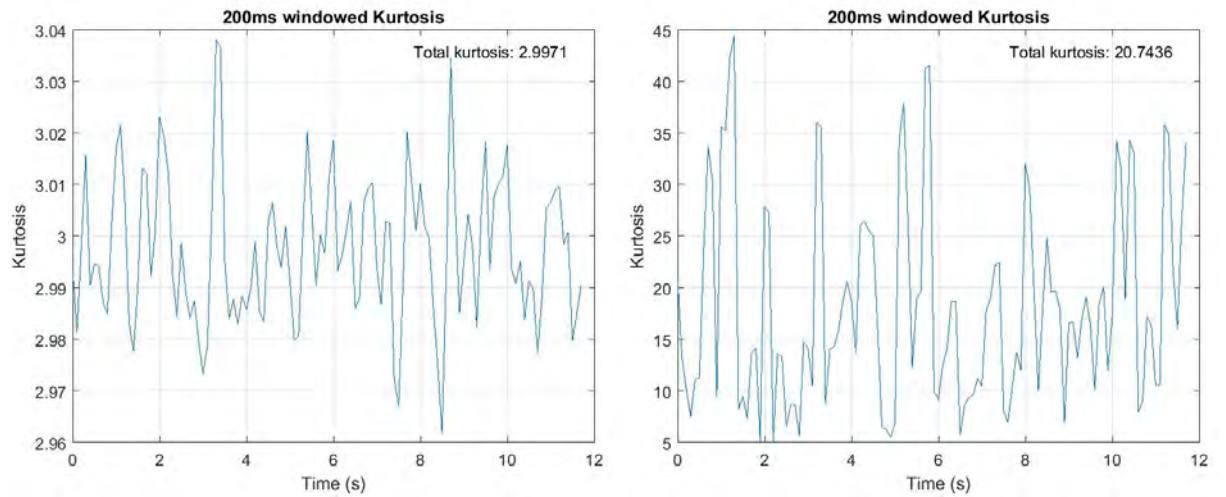


Figure 4.6: Kurtosis calculated for two different vibration signal recorded from wind turbines.

4.3.2 Frequency domain analysis

Using frequency domain signal processing techniques are popular and reliable as using these methods one would be able to detect the exact location of the defects on simple rotating machinery. Using this technique it would be possible to break down the time domain signal into different frequency components [112, 120] Figure 4.7 shows the four frequency-domain signal analysis techniques that are going to be discussed in this part.

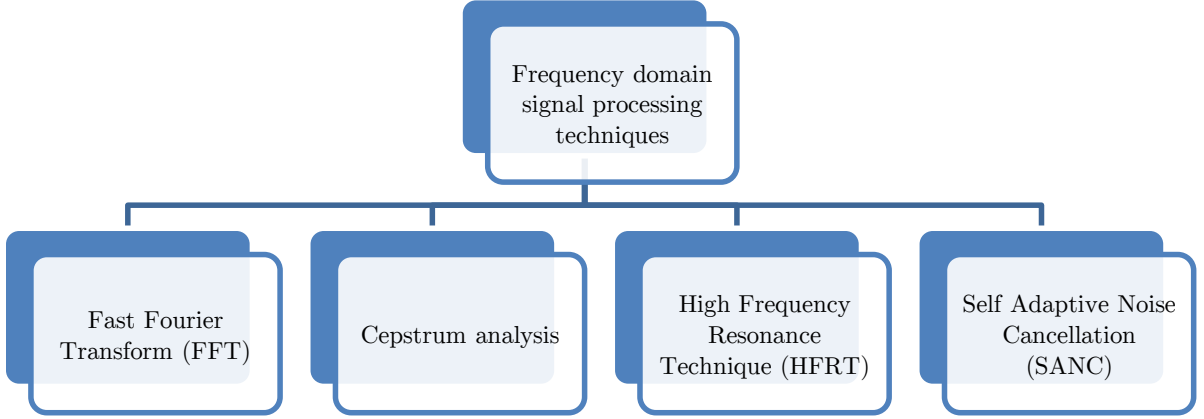


Figure 4.7: Summary of Frequency domain signal processing techniques.

Fast Fourier Transform

To separate the constituent features of a signal Fast Fourier transform can be used. The FFT algorithm decomposes the signal into its constituent frequencies moving from time-domain into frequency-domain or spectrum of the signal.

For a continuous signal which is the input signal, this conversion will be done by using equation 4.7 over the finite time window then the signal would be digitized and saved. The Discrete Fourier Transform (DFT) of the signal is the frequency spectrum of the signal indeed and each line of the frequency spectrum is known as the component of the signal.

$$X(f) = \int_{-\infty}^{+\infty} x(t)e^{-j2\pi ft} dt \quad (4.7)$$

The Inverse Fourier Transform (IFT) formula can be used to convert the FD signal back to the TD signal using equation 4.8

$$x(t) = \int_{-\infty}^{+\infty} X(f)e^{j2\pi ft} df \quad (4.8)$$

Signal analysis in the frequency domain provides more information regarding the signal nature in comparison with analysis in time domain therefore it is more reliable and efficient.

Figure 4.8 shows an example of FFT calculated on a vibration signal recorded from a bearing. The damage of bearing is visible in the spectrum and is marked.

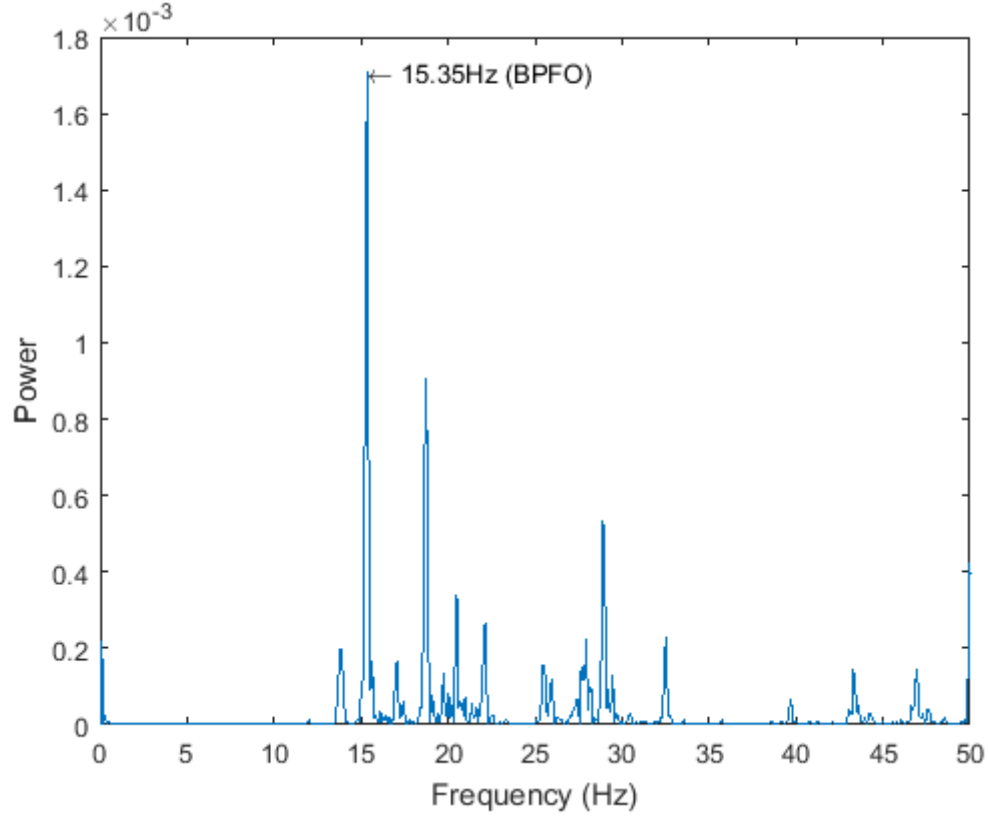


Figure 4.8: Fast Fourier Transform of the vibration signal recorded from faulty bearing.

Cepstrum Analysis

Cepstrum analysis is a data analysis method which is recommended for analysing data containing wavelet and repeated patterns in a spectrum [121,122] Bogert et al [123] originally developed Cepstrum in 1963 as a better option than autocorrelation function to detect the echo delay times. The most important application of the Cepstrum analysis in industry regarding to machine diagnosis is gearbox defect analysis [123]. Cepstrum analysis is able to separate the impulse response from excitation forces. Therefore, it can be a useful tool for rendering vibration signals containing defects more distinguishable in the spectrum [124]. The Cepstrum is the power spectrum of the logarithm of the power spectrum where the power spectrum is the “Inverse Fourier Transform of the log power

spectrum [122]”.

Cepstrum terminology is summarised in Table 4.1

Table 4.1: Terminology of Cepstrum analysis after [125].

Spectrum	Cepstrum
Frequency	Quefreny
Magnitude	Gamnitude
Phase	Saphe
Harmonic	Rahmonic
Filter	Lifter
Fundamental	Mundafendal

From Table 4.1 can be seen that the terms, Cepstrum, quefreny, Gamnitude, saphe, Rahmonic, lifter and Mundafendal are anagrams of spectrum, frequency, magnitude, phase, harmonic, filter and fundamental.

High Frequency Resonance Technique HFRT

One of the common problems in signal processing is the presence of various interferences and noises in the signal. This can be due to noisy environment or the recording sensor being too close to the other components. Therefore, the signal will be recorded along with other features from various parts of gearbox components and background noise. In these situations the identification of the signal belonging to the faulty part could be very difficult or even impossible due to presence of other features [126].

One technique to address this issue is the high frequency resonance technique (HFRT) which is also known as envelope analysis. In this technique prior to performing FFT of the signal few extra steps will be taken to reduce the effect of unwanted features. These steps include band pass filtering of the original signal to a small bandwidth and extracting the envelope of the signal. The filtering procedure removes most of the high frequency and unwanted features from the original signal while the envelope detection will further clean the data by removing sudden and sharp peaks due to the noise in the signal. After these

steps obtaining the signal spectrum will lead to much cleaner and more distinct frequency components and therefore better diagnosis [126].

Figure 4.9 shows the block diagram of high frequency resonance technique procedure.



Figure 4.9: High Frequency Resonance Technique algorithm.

Extracting the envelope of the signal is usually done either using squaring and low pass filter or Hilbert transform.

Squaring and low pass filtering method involves squaring the input signal to demodulate it using itself and then passing it through low pass filter to remove the high frequency content of the signal which leads to creation of a signal which is envelope of the actual signal.

Envelope detection using Hilbert transform is a technique to create an analytic signal for the input signal using Hilbert transform. The mathematical definition of the envelope ‘env’ is

$$env(t) = \sqrt{signal(t)^2 + H(t)^2} \quad (4.9)$$

Where signal is defined as the original input signal and H(t) is the Hilbert transform of the input signal.

Self-Adaptive Noise Cancellation

Self-adaptive noise cancellation technique which is also known as SANC, is an expansion to the original technique that is adaptive noise cancellation ANC. The aim of this technique

is to separate two mixed signals from one another with the assumption that these signals are uncorrelated. In general, the unwanted features in the signal are constituting noise are subtracted (removed) as noise features from the other signal. Figure 4.10 shows the schematic diagram of the adaptive noise cancellation algorithm. This algorithm requires prior knowledge of the noise features that are going to be removed. In the case of the present project, this technique can be used to separate the gear and bearing signals that are superimposed on one another. This can be done by assuming either gear signal or bearing signal as noise and subtract it from the mixture. The reference signal can be recorded from an individual bearing or gear with similar specification and fed into the system. Then it will be modified adaptively to remove as much noise as possible from the mixed signal. This is done simply by relying on the assumption that these two signals are uncorrelated and minimisation of the variance will lead to better removal of the noise from the mixed signal [127].

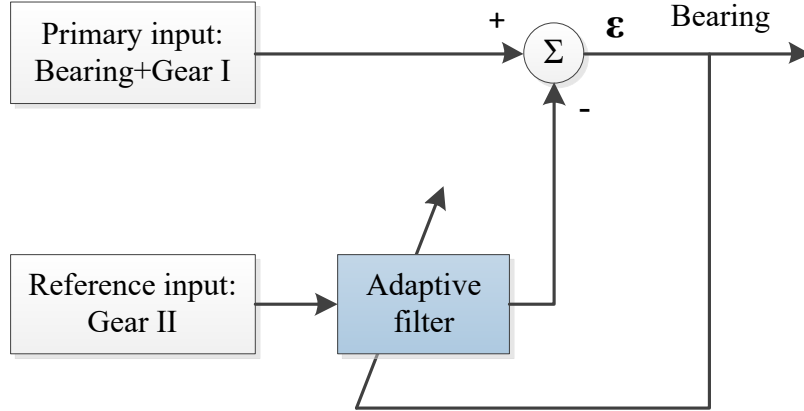


Figure 4.10: Diagram of Adaptive Noise Cancellation (ANC) [127].

One drawback of ANC technique is that it is not always possible to have a reference signal to subtract from the mixed signal. To overcome this issue, the SANC technique has been developed which is independent to the reference signal. As it is shown in Figure 4.11 the SANC technique uses the same mixed input signal to remove the unwanted source from the mixed signal. This is done by delaying the mixed signal with a constant time δ and feed it to the system as the reference signal. This is particularly useful for removing

random signals such as white noise from a deterministic (discrete frequency) recorded signal. If the delay is long enough in the sense that it is longer than the correlation of the random signal, the adaptive filter will not recognise the relation of the random signal and will only find the transformation between the deterministic signal and the delayed version of that signal and thus removes the random noise [127].

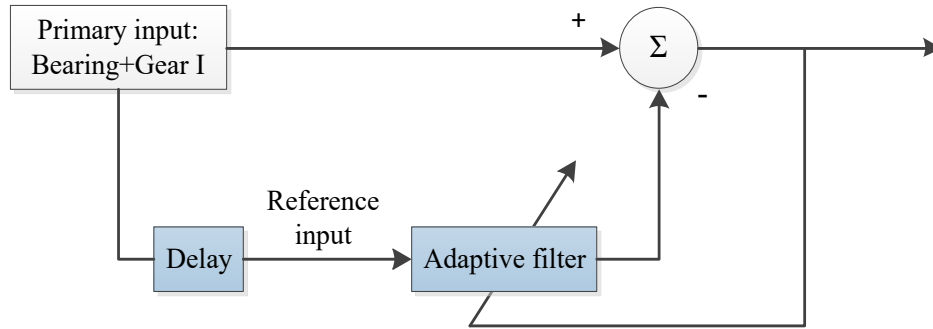


Figure 4.11: Diagram of Self-adaptive Noise Cancellation (SANC) [127].

This technique can be used to minimize the background noise of the signal and improving the visibility of the different signal components in the spectrum [128]. In signal processing techniques, the self-adaptive noise cancellation can be very useful to clean the noise from the recorded signal before envelope detection to obtain a clean envelope that is not contaminated with noise. Figure 4.12 shows the schematic diagram of the SANC technique in conjunction with envelope analysis.

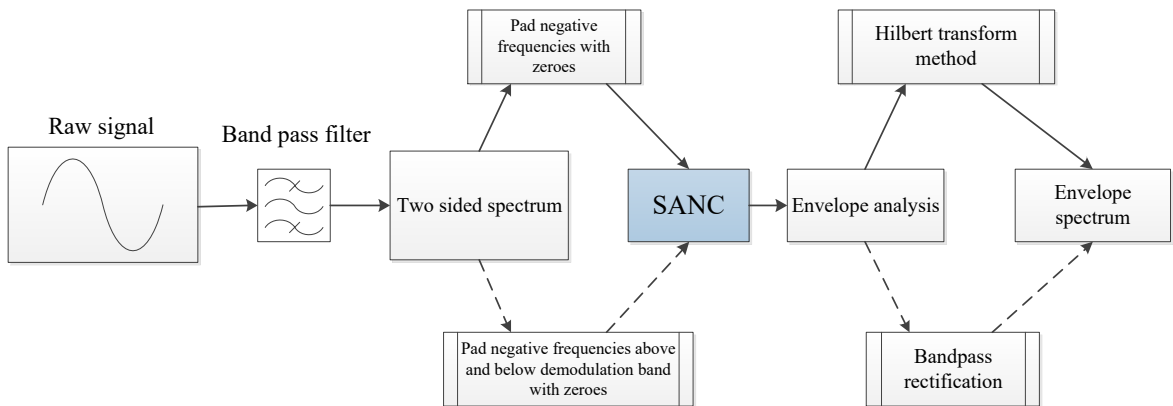


Figure 4.12: Schematic diagram of SANC technique in conjunction with envelope analysis after [129].

4.3.3 Mixed-mode and advanced techniques

Short Time Fourier Transform (STFT)

The short time Fourier transform is a form of Fourier transform but extra information about the time domain is provided, making this algorithm a very powerful signal processing tool. To perform a short time Fourier transform, the data, $f(x)$ is divided into smaller parts using a fixed window, $g(x)$. The selected window is moved forward with some overlap relative to the previous window. A normal FFT will be performed on each window and the final result will have both time and frequency domain information linked [130] as shown in Figure 4.13. The result from an actual tidal turbine is presented in Figure 4.14.

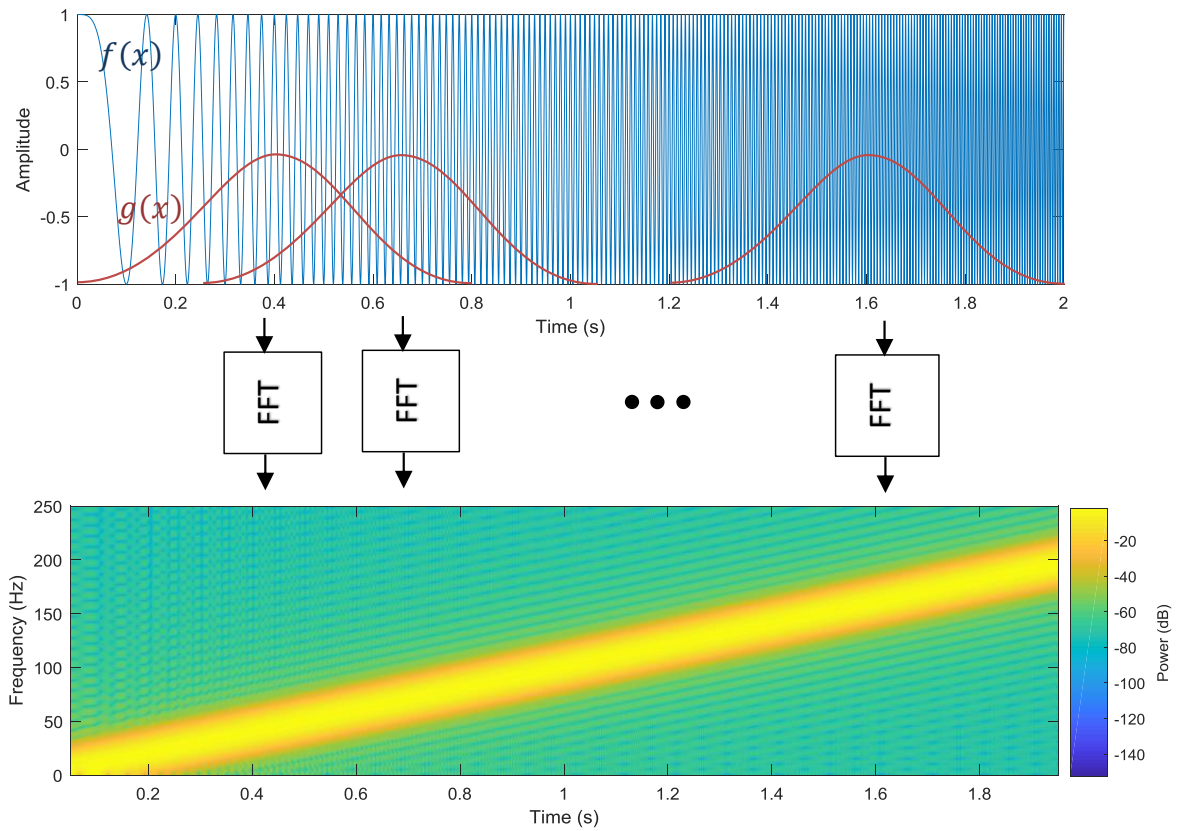


Figure 4.13: Short time Fourier transform.

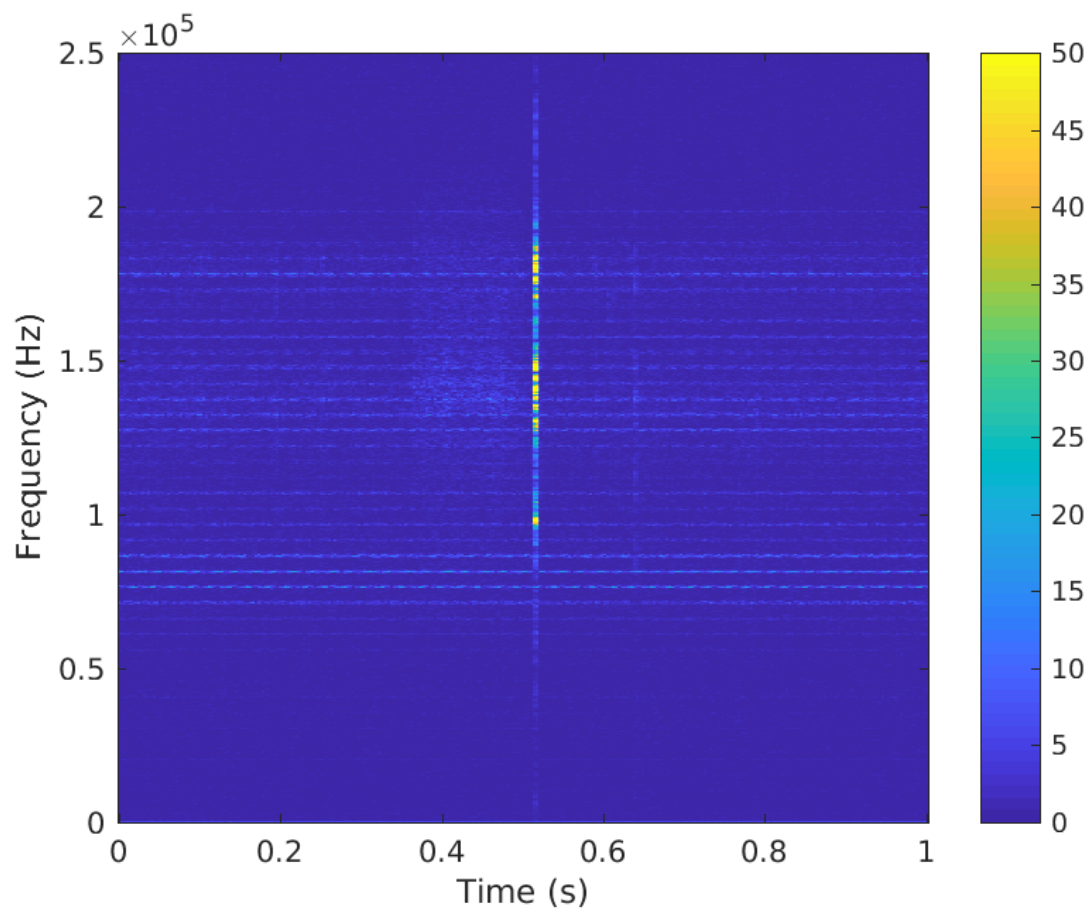


Figure 4.14: Short time Fourier transform of vibration signal recorded from a Tidal turbine, showing an impact on the blades at around 0.5 seconds.

Wavelet Transform (WT)

Wavelet transform is a similar technique to the Fourier transform and project the signal to a set of functions. However, unlike the Fourier transform, that decompose the signal into sine and cosines, wavelet transform functions are named wavelet [131]. A wavelet function can be viewed as a truncated sine wave as shown in Figure 4.15. However, there are many different wavelet functions that are not similar to sine wave. One of the key parameters in the short time Fourier transform is the length of the window used to perform the FFT. There is a trade-off between the window length and resolution. Using shorter window will increase the time resolution but the frequency resolution will decrease. Similarly, increasing the window length will increase the frequency resolution and decrease the time resolution. The wavelet transform can address this issue by changing the window length as shown in Figure 4.16. The result from an actual tidal turbine experiencing an impact on its blades is presented in Figure 4.17.

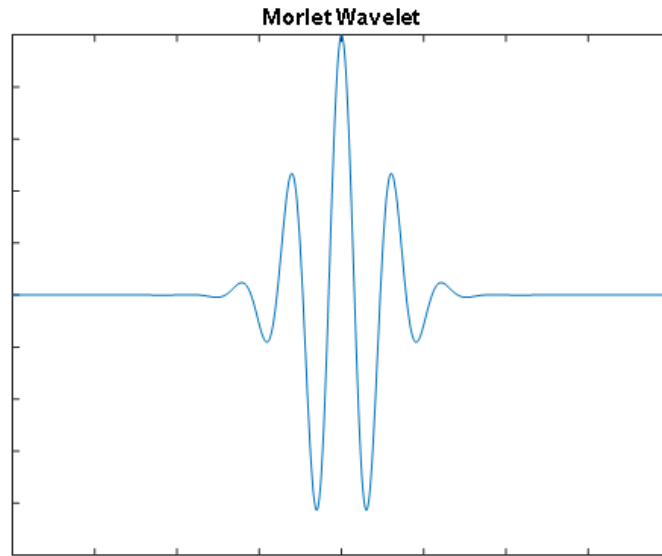


Figure 4.15: An example of wavelet wave function known as Morlet.

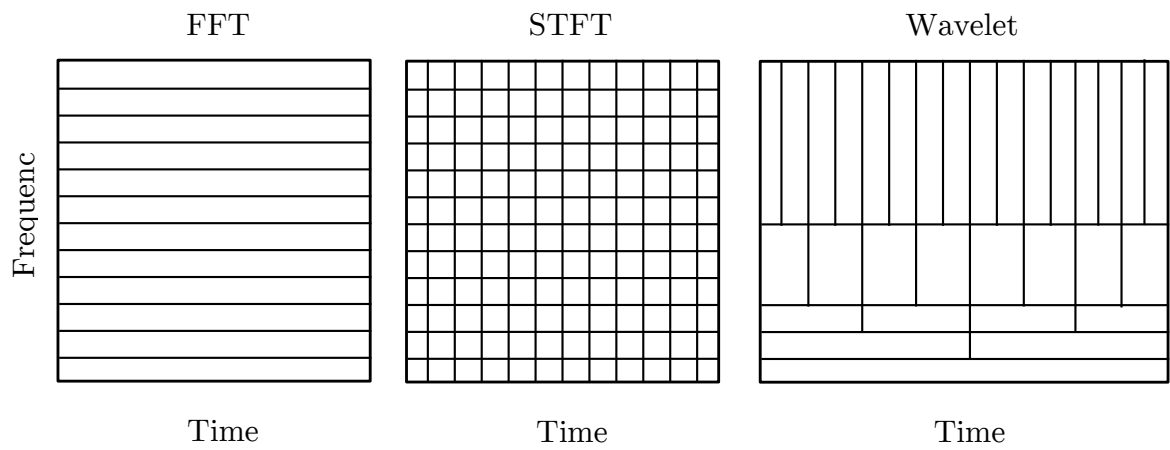


Figure 4.16: The difference between FFT, STFT and Wavelet.

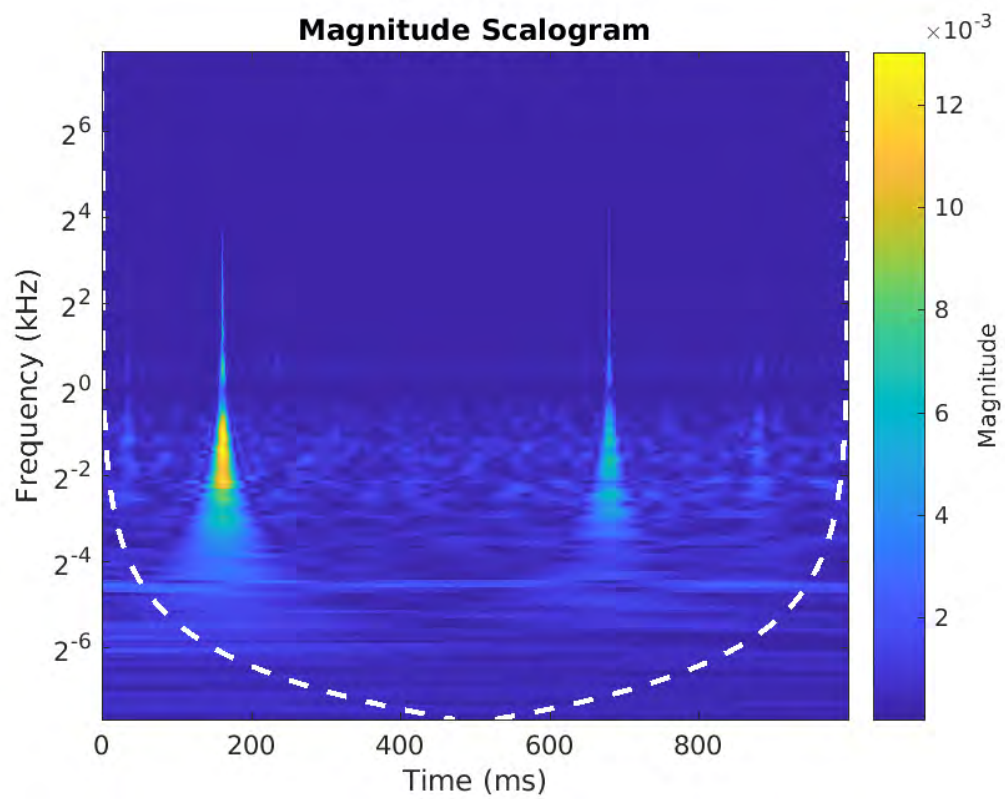


Figure 4.17: Wavelet transform of acoustic signal recorded from a Tidal turbine, showing an impact on the blades at around 200 milliseconds.

Spectral Kurtosis

Spectral Kurtosis is a statistical tool that can indicate non-Gaussian components in a signal as well as the location of the non-Gaussianity in the frequency spectrum. This is a useful algorithm that can provide additional information to the classical second order power spectral density [132, 133]. This algorithm was originally defined as normalised fourth-order moment of the real part of the short-time Fourier transform and later on was modified to take the magnitude instead of real part. This algorithm can be used as filter to retrieve randomly occurring signals that are heavily distorted by additional stationary noise [132]. Figure 4.18 shows an example of spectral kurtosis to identify transient in a noisy signal.

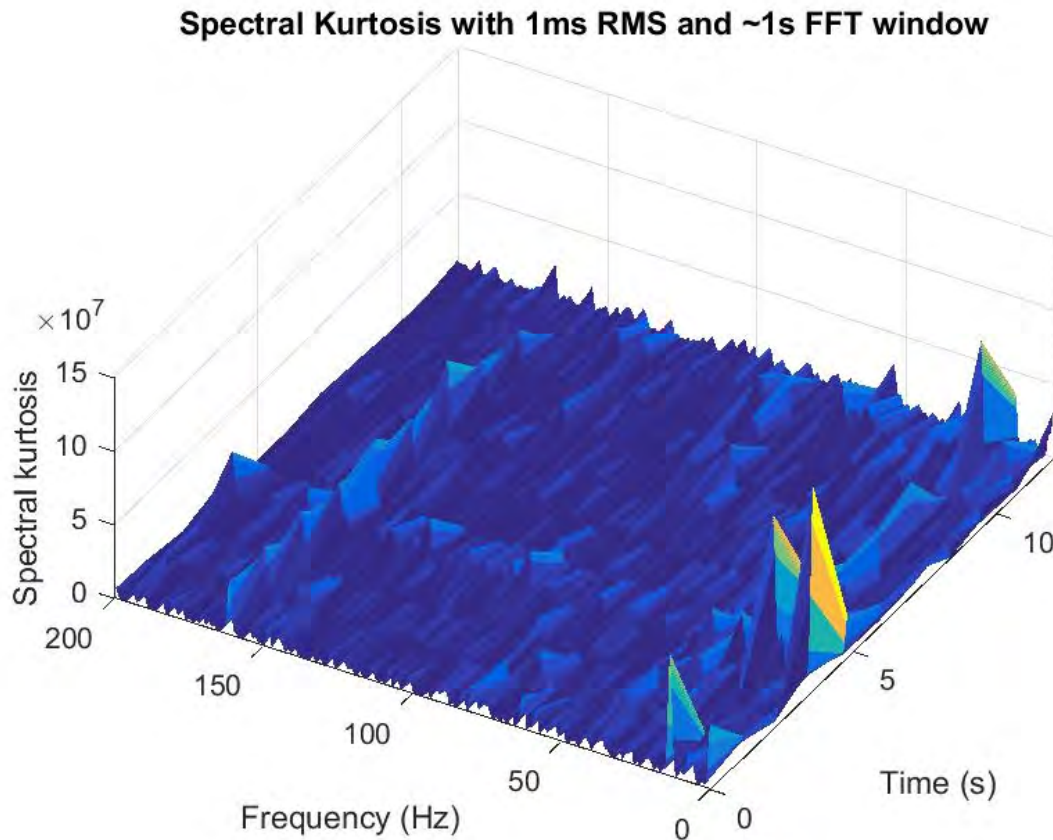


Figure 4.18: Spectral kurtosis of a faulty wind turbine, showing peaks at planetary frequencies and around 5 s and lower peaks at around 170Hz corresponding to BPFO of the high speed shaft.

Kurtogram Analysis

The Kurtogram is a fourth-order spectral kurtosis analysis tool which is derived from spectral kurtosis. The Kurtogram was first introduced by Antoni and Randall in 2005 [133,134]. It has been used to detect and characterise non-stationaries behaviour in signal. Kurtogram is a very useful and powerful tool in machinery defect detection [134,135].

The model claims that each type of transient is related with the best dyadic relationship ($f; \Delta f$) which maximises its kurtosis, and therefore its recognition [134]. The goal of Kurtogram is to find the centre frequency, and the bandwidth of a band pass filter [134] to extract information from the original signal. Figure 4.19 shows Kurtogram applied on a real data recorded from a wind turbine. The bright yellow square in the graph shows high amount of kurtosis at that band of frequency.

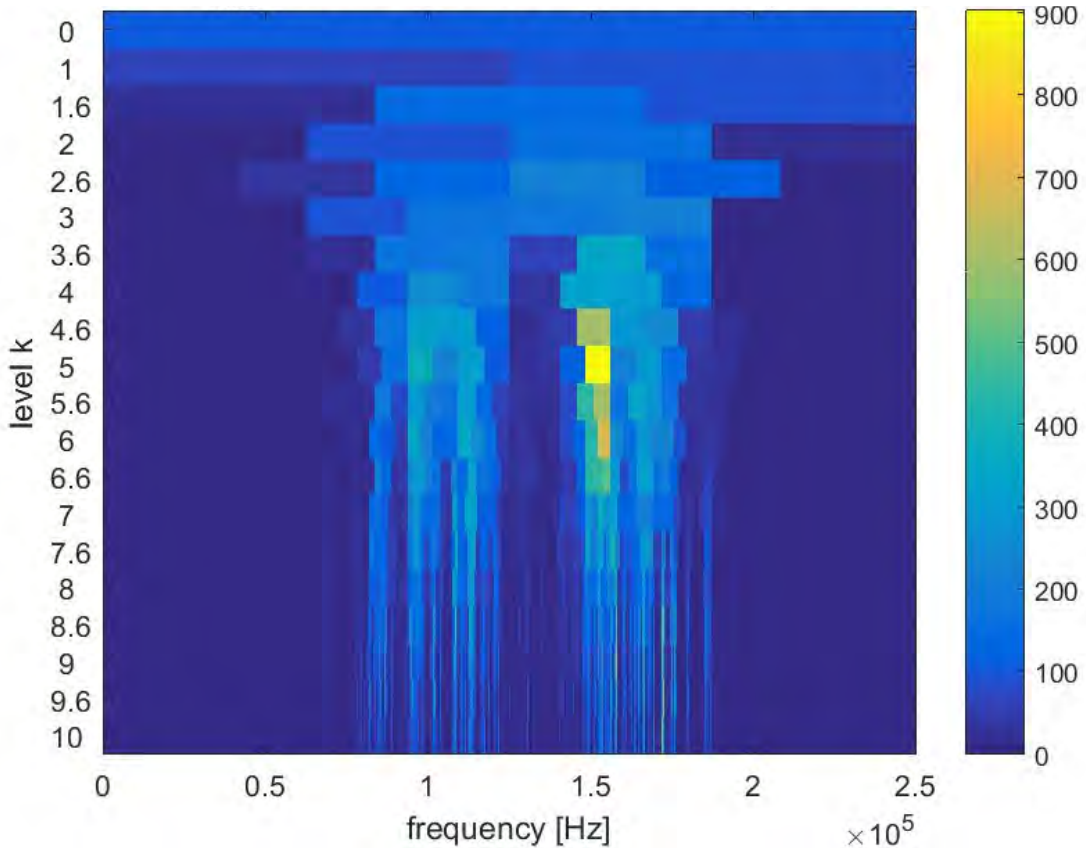


Figure 4.19: The Kurtogram calculated on Acoustic emission signal recorded from a faulty wind turbine, identifying high level of kurtosis at a band with centre frequency of 150 kHz and a bandwidth of about 8kHz (level 5).

Maximum Correlated Kurtosis Deconvolution (MCKD)

The Maximum Correlated Kurtosis Deconvolution technique was first proposed by McDonald et al. in 2012 for gear fault detection [136]. It is relying on the periodic nature of the fault in the signal and the impulse-like signal that is produced by such faults and tries to find a finite response filter to maximise the correlated kurtosis of the signal [137].

Consider a discrete signal $x(n)$ and a gear fault signal added to the signal as $y(n)$. The MCKD technique tries to find a finite response filter $f(l)$ such that the correlated kurtosis of the recovered fault signal $y(n)$ is maximised:

$$y(n) = \sum_{k=1}^L f(k)x(n-k+1) \quad (4.10)$$

where l is the length of the filter.

The deconvolution norm proposed by McDonald et al. is defined as

$$\begin{aligned} \text{Correlated Kurtosis of } M - \text{Shift} &= CK_M(T) \\ &= \frac{\sum_{n=1}^N (\prod_{m=1}^M y(n-mT))^2}{(\sum_{n=1}^N y^2(n))^{M+1}} \end{aligned} \quad (4.11)$$

that enhances the filter output periodicity at a period equal to T and increased kurtosis. Here N is the number of samples in signal x and T is the period. In the special case of $T=0$ and $M=1$, the equation simplifies to kurtosis norm used for Minimum Entropy Deconvolution [136].

MCKD is defined as maximum of equation 4.10, $MCKD_M(T) = \max_{f(l)} CK_M(T)$ and is calculated by solving

$$\frac{d}{df(t)} CK_M(T) = 0 \quad (4.12)$$

Using matrices.

Empirical Mode Decomposition (EMD)

The Empirical Mode Decomposition (EMD) is the fundamental part of a technique known as Hilbert-Huang Transform that is an empirical data analysis technique, developed in late 1990's by Huang et al. [138–140].

Unlike other techniques such as Fourier or Wavelet Transforms, that use prior knowledge or fixed basis to decompose the signal, EMD derives its basis adaptively from the data itself and does not rely on any prior knowledge [141]. This technique is based on an assumption that any data is consisting of a set of simple intrinsic modes of oscillations [142].

The EMD decomposition process, decompose the original signal into a set of signals known as Intrinsic Mode Functions (IMFs). This is accomplished by a novel process known as “sifting” which is repeatedly applied to the signal until it converges on criteria that defines an IMF [141]. The EMD sifting process extracts the fastest varying component first and continues to the next IMF. The process produces a finite number of IMFs before converging itself.

The extracted IMFs represent simple oscillatory functions with different time-scale. Each IMF by definition will have the same number of extrema and zero-crossings or differ at most by one. Furthermore, the mean value of the envelopes of local maxima and local minima of IMFs are zero at any given point [140].

The technique to calculating the IMFs are briefly explained here but for more details and derivations on the technique one can refer to [138, 142].

The first step to calculate the IMF is to find all the local maxima points of the signal and connect them using cubic spline to obtain the upper envelope of the signal.

The same procedure is applied to the local minima points to obtain the lower envelope. Next, the mean value of the two envelopes is calculated. The first component of the signal

is calculated by subtracting the obtained mean from the original signal

$$h_1(t) = x(t) - m_1(t) \quad (4.13)$$

where $x(t)$ is the original signal and m_1 is the calculated mean. If the calculated component h_1 meet the IMF criteria, then it will be the first IMF. However, if the calculated component does not meet the requirement of an IMF, the procedure is repeated again by replacing the original signal $x(t)$ with h_1 . This cycle is repeated until the calculated component meet the IMF criteria. It is then marked as the first IMF (c_1) and subtracted from the original signal.

$$x_{new}(t) = x(t) - c_1(t) \quad (4.14)$$

After this step the original signal $x(t)$ is replaced with the new signal $x_{new}(t)$ and the whole procedure is repeated to calculate the next IMFs. The remaining signal after calculating the last IMF is usually called the residual signal $r(t)$ and can be used to reconstruct the original signal using the calculated IMFs using

$$x(t) = \sum_{i=1}^n c_i(t) + r(t) \quad (4.15)$$

where n represent the number of calculated IMFs. This process is summarised in Figure 4.20. Although this technique is very effective in decomposing non-linear and non-stationary signals, it suffers from certain problems such as end effect or mode mixing (aliasing) which was noted by Huang himself [140].

One solution to avoid the mode mixing problem is to use a newly proposed technique known as Ensemble EMD (EEMD) [143]. This technique uses noise assisted analysis to solve the problem of mode mixing in the EMD algorithm.

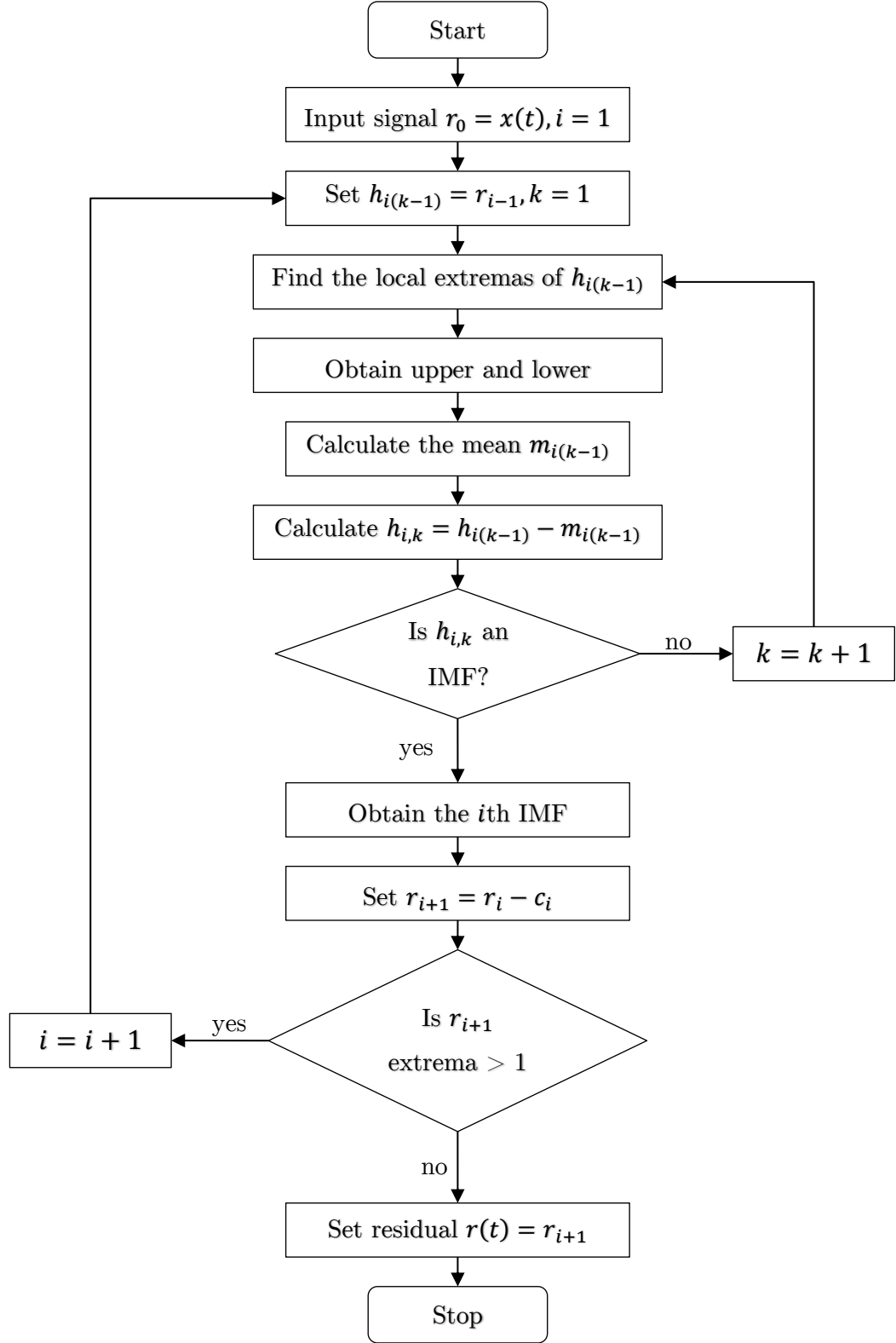


Figure 4.20: The procedure to obtain IMFs using EMD technique.

Ensemble Empirical Mode Decomposition EEMD

As it was discussed in the previous section, EMD suffers from mode mixing or aliasing. To overcome this problem a White Gaussian noise is added to the signal. Consider adding noise to the proposed signal for M times and each time decomposing the signal using EMD technique. Each new signal can be presented as

$$x_i(t) = x(t) + w_i(t) \quad (4.16)$$

where $w_i(t)$ represents the i-th added white noise to the original signal $x(t)$ and $x_i(t)$ is the generated noisy signal. Using equation 4.15 one can reconstruct the i-th noisy signal as

$$x_i(t) = \sum_{j=1}^M c_{ij}(t) + r_i(t) \quad (4.17)$$

where c_{ij} is the j-th calculated IMF of noisy signal $x_i(t)$. Now it is possible to ensemble the corresponding IMF over noisy signals to obtain the resulting IMFs

$$c_j = \frac{1}{M} \sum_{i=1}^M c_{ij} \quad (4.18)$$

where M is the total number of times that the white noise was added to the signal.

The accuracy of the result obtained using EEMD is highly dependent on the number of ensemble and the amplitude of the added noise ε , Using a well-established statistical rule such as equation 4.19, the standard deviation of error ε_n in the final IMFs can be calculated [22]. A decomposed signal using this technique is presented in figure 4.21.

$$\varepsilon_n = \frac{\varepsilon}{\sqrt{N}} \quad (4.19)$$

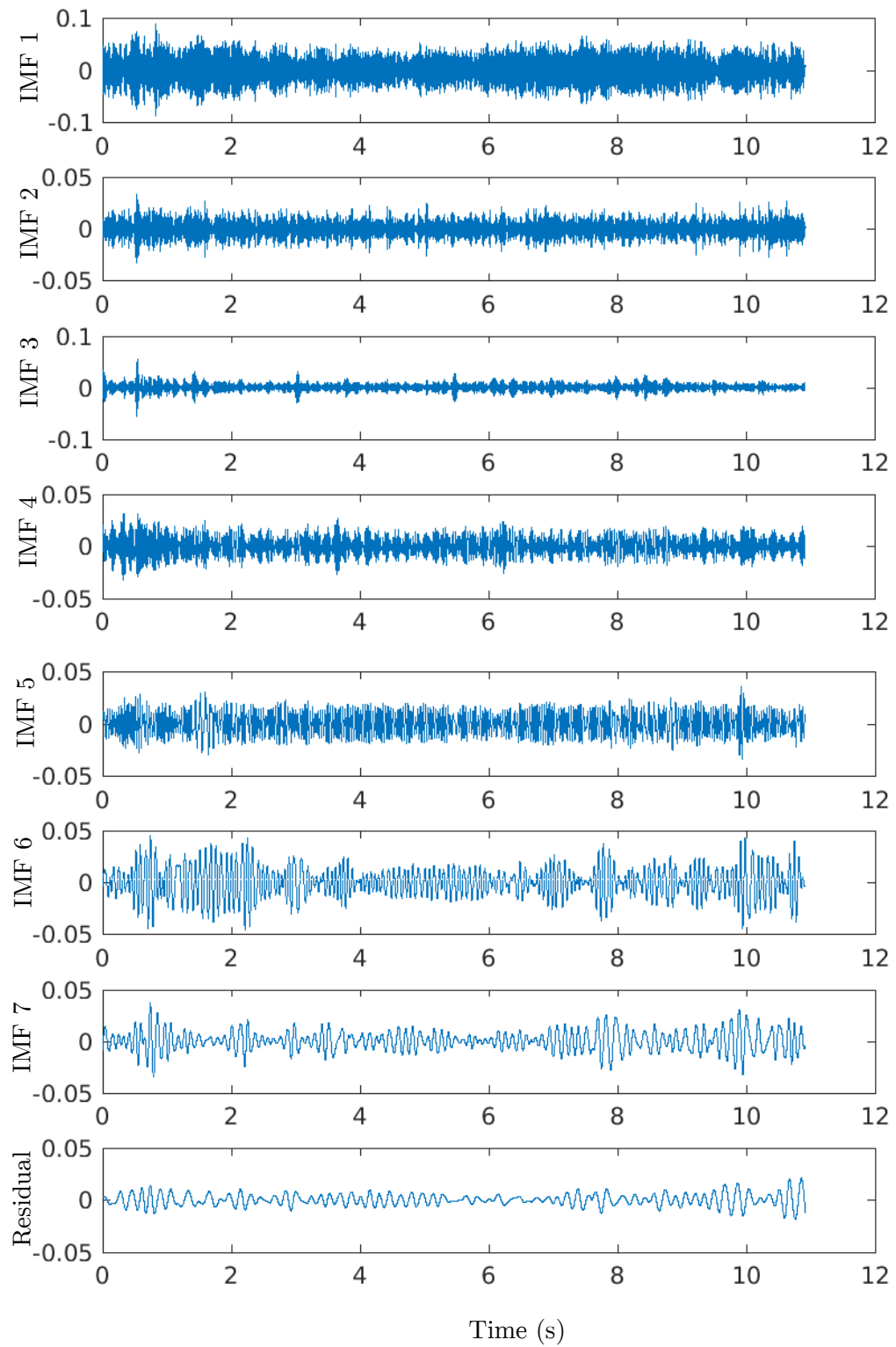


Figure 4.21: IMF decomposition applied to vibration signal recorded from high speed shaft of a wind turbine.

Cyclo-stationary signals

The cyclostationary concept was developed 40 years ago [144, 145]. In recent years, cyclostationary theory has been increasingly used in the field of mechanical fault detection. Vibration signals extracted from bearings and rotating machines are non-stationary signals containing some hidden periodicities in their background. Cyclostationary signal analysis is a very powerful technique [146].

The statistics of cyclostationary signals have periodicity with respect to time [147]. Currently, second-order cyclostationary which is called cyclic correlation [147] has an important role in practical applications. Despite the effectiveness of this technique and its popularity in signal processing of signals obtained from rotating machinery, it has not attracted much attention in the field of wind turbine condition monitoring and signal processing so far.

In general, a random process will have a time-varying autocorrelation:

$$R_x(t, \tau) = E \left\{ x \left(t + \frac{\tau}{2} \right) x^* \left(t - \frac{\tau}{2} \right) \right\} \quad (4.20)$$

where $E\{x\}$ denotes the mathematical expectation operator, and τ is the time delay. Now, if the autocorrelation is considered periodic with a period of T_0 , the ensemble average can be estimated with a time average as below:

$$R_x(t, \tau) = \lim_{N \rightarrow \infty} \left\{ \sum_{-N}^N x \left(t + nT_0 + \frac{\tau}{2} \right) x^* \left(t + nT_0 - \frac{\tau}{2} \right) \right\} \quad (4.21)$$

The autocorrelation function in equation 4.20 can be written in form of Fourier series due to its periodicity

$$R_x(t, \tau) = \sum_{\alpha} R_x^{\alpha}(\tau) e^{j2\pi\alpha t} \quad (4.22)$$

where $\alpha = m/T_0$ and $m \in \mathbb{Z}$.

Combining the above equation with the equation 4.21, one can write the Fourier

coefficients as below

$$\begin{aligned} R_x^\alpha(\tau) &= \lim_{T \rightarrow \infty} \frac{1}{T} \int_{-\frac{T}{2}}^{\frac{T}{2}} x\left(t + \frac{\tau}{2}\right) x^*\left(t - \frac{\tau}{2}\right) e^{-j2\pi\alpha t} dt \\ &= \left\langle x\left(t + \frac{\tau}{2}\right) x^*\left(t - \frac{\tau}{2}\right) e^{-j2\pi\alpha t} \right\rangle_t \end{aligned} \quad (4.23)$$

where $R_x^\alpha(\tau)$ is known as cyclic autocorrelation function with α being the cyclic frequency. The $\langle \dots \rangle$ symbol represents the time averaging operator. Next, to obtain the cyclic spectrum, one could apply the Fourier transform to the cyclic autocorrelation function with respect to the time delay τ , yielding

$$S_x^\alpha(f) = \int_{-\infty}^{\infty} R_x^\alpha(\tau) e^{-j2\pi f\tau} d\tau \quad (4.24)$$

that is known as cyclic spectrum or the spectral correlation function.

The cyclic coherence that measures the strength of the correlation between spectral components distanced by cyclic frequencies can be calculated using [148].

$$C_x^\alpha(f) = \frac{S_x^\alpha(f)}{\sqrt{S_x^0\left(f + \frac{\alpha}{2}\right) S_x^0\left(f - \frac{\alpha}{2}\right)}} \quad (4.25)$$

Figure 4.22 shows the Cyclic Spectral Coherence calculated for a faulty bearing with damaged inner race. The characteristic frequency of BPFI is clearly visible in the calculated result.

4.4 Summary

In this chapter the common condition monitoring techniques such as vibration and acoustic signals were reviewed and suitability of each of the techniques for fault detection were investigated. Common signal processing techniques used on recorded data from the turbines were also discussed. Next chapter will utilise these condition monitoring and signal

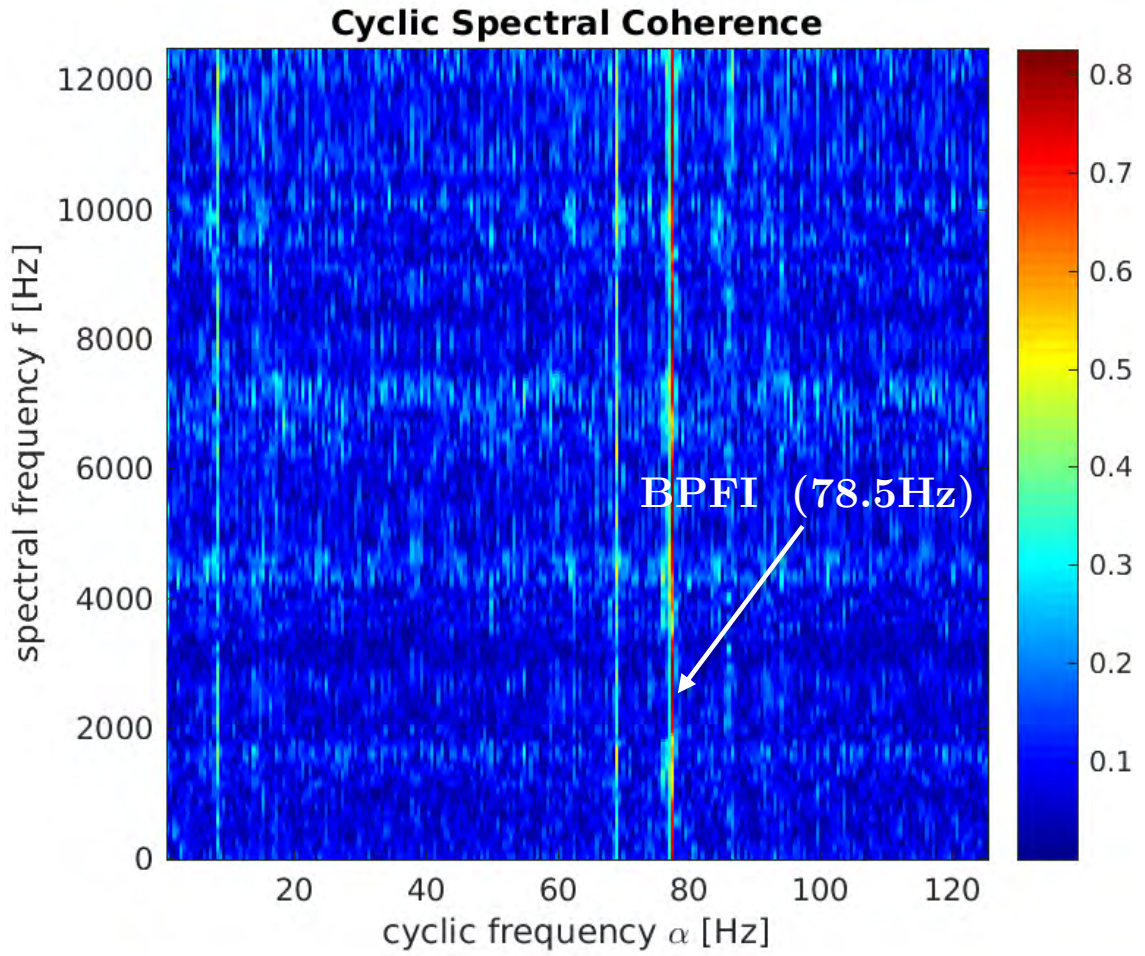


Figure 4.22: The cyclic spectral coherence calculated for a faulty bearing, showing the BPFI characteristic frequency at 78.5Hz.

processing techniques in the controlled environment to evaluate the performance of each of these techniques to detection known faults in the gearbox.

“A theory can be proved by experiment”
— *Albert Einstein*

Chapter 5

Controlled environment testing

5.1 Introduction

In the previous chapter various signal processing techniques were discussed and explored. Each signal processing technique has their own advantages and disadvantages. It is almost impossible to detect all type of faults with only one signal processing technique. Any signal processing technique is suitable to detect certain type of faults and may not detect other types of faults. Thus, they have to be used in conjunction with each another to provide a comprehensive diagnostic of the system.

This chapter focuses on the vibration and acoustic emission data recorded from controlled sources under known conditions. This helps to understand the limitations and capabilities of the various signal-processing techniques to identify the faults in a controlled situation.

The data required for this part has been obtained from two distinct sources. The first source is a bearing test rig in the laboratory with controlled load and speed. The second source is the data recorded from a more complex 3-stage gearbox in a mock-up tidal turbine.

5.2 Measurement setup and instrumentation

5.2.1 Bearing test-ring

This test-rig has been developed over the past years specifically for measurement of bearings defects using both acoustic emission and vibration sensors at the University of Birmingham. This test-rig consists of mechanical and electrical parts. The mechanical part consists of four components; the driver (i.e. DC motor), translation components (pulleys, belt and shafts), bearing load, and load control. This is illustrated in Figure 5.1. The electrical part consists of the following components as below:

- Control unit
 - DC motor controller
 - Tachometer and speed controller
- Sensors
 - Acoustic: an R50 α acoustic emission sensor by Physical Acoustic Corporation with a peak sensitivity of -62dB and operation frequency of 100-700 kHz.
 - Acceleration: High frequency 712F accelerometer by Wilcoxon Corporation with a nominal range of 3 Hz to 25 KHz.
- Amplifiers and connectors
 - Voltage pre-amplifier 2/4/6 by Physical Acoustic Corporation with selectable 20, 40 or 60dB gain (used for acoustic sensors).
 - Feldman Enterprises 4 channels measurement hub
 - AE5A amplifier by Physical Acoustic Corporation with 10kHz to 5MHz bandwidth and a selectable gain from 0 to 41dB.
 - Vibra-Metrics LP241-12 accelerometer power box

- Data acquisition
 - Agilent U2531A 4 channels DAQ with 14bits resolution with a sampling rate of 2Mega-Samples per second.
- Data recording
 - A personal computer equipped with USB port connected to the DAQ unit
 - Developed MATLAB software to record the data from DAQ.

This test-rig has the ability to apply a pressure up to 8 bar (116 PSI) to the bearing with controlled rotational speed up to 1000 RPM (17Hz). The sensors were mounted on the bearing using magnetic hold-downs and glue for coupling as shown in Figure 5.2

To record the vibration signal the sensor will be connected to a pre-amplifier for initial low noise amplification of the signal and the output will be connected to the amplifier for further amplification. The output of the amplifier then will be connected to the signal hub to join different sensors into one cable to be connected into the data acquisition unit. Finally, the data acquisition unit will be connected to the computer via USB port and customised software will record the data into the files for storage and further processing. This set-up has been shown in figure 5.3

5.2.2 Gearbox test-rig

This test-rig has been developed by TWI and the Brunel University to replicate a tidal turbine with the ability to be submerged into the water. It consists of a three-phase 750 W AC motor controlled by a Variable Frequency Driver (VFD). This developed equipment has been shown in figure 5.4. This test-rig is equipped with two acoustic emission sensors in X and Y directions mounted with magnetic hold-downs on the gearbox to record any vibration. Similarly, two accelerometers mounted along the X and Y directions on the input shaft of the gearbox over the bearing to record vibration data. The locations of the sensors were chosen in such a way that they are as close as possible to the component

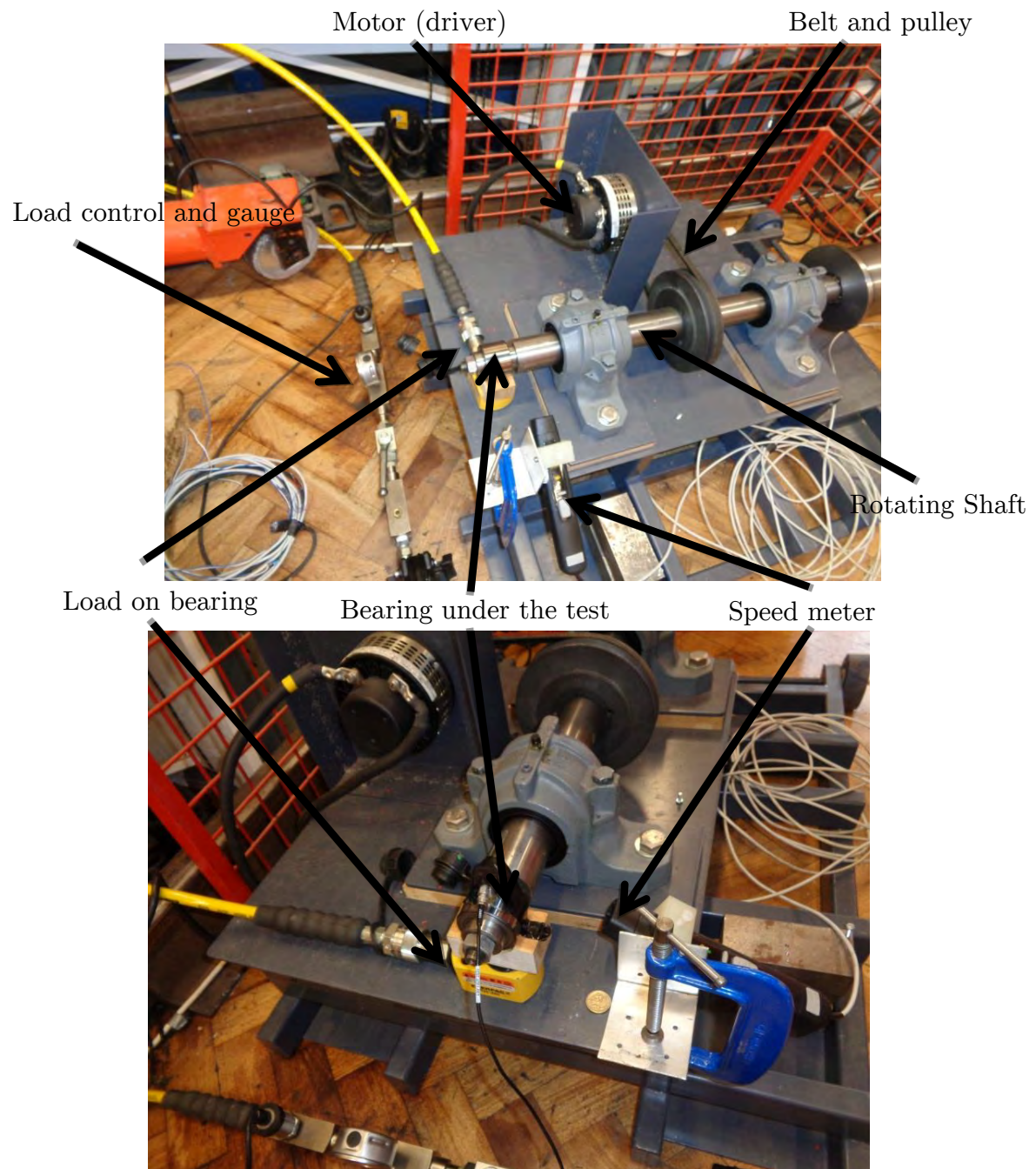


Figure 5.1: Controlled test-rig for bearing defect measurement developed at the University of Birmingham

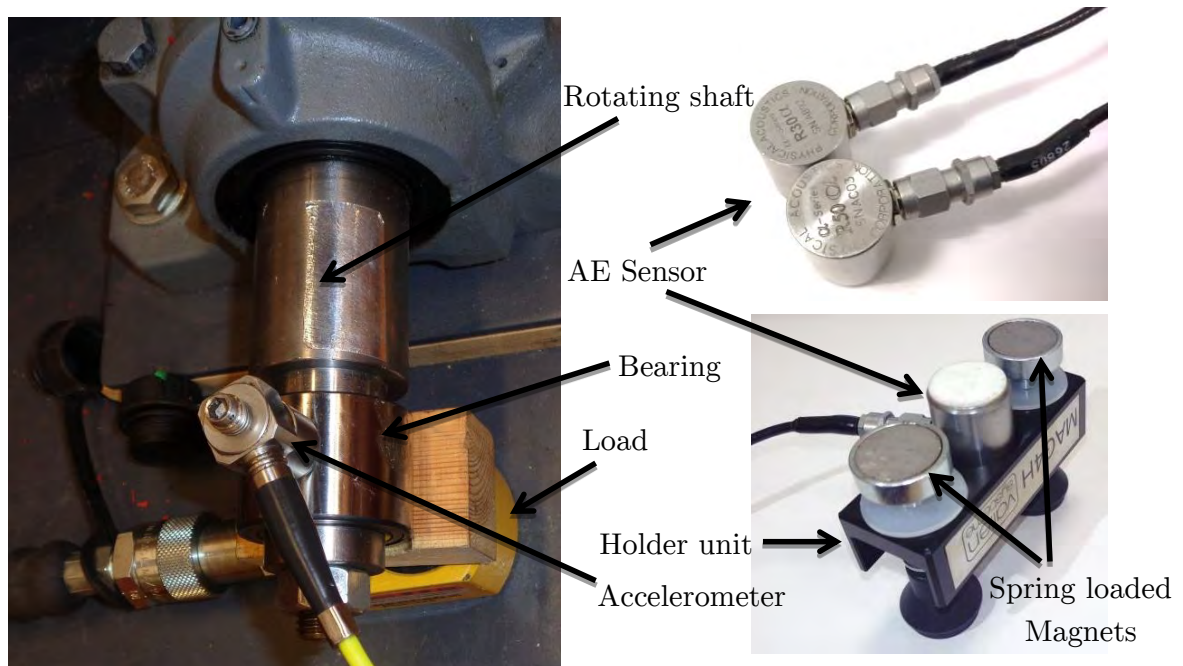


Figure 5.2: Bearing acoustic emission and vibration test-rig and sensor representation

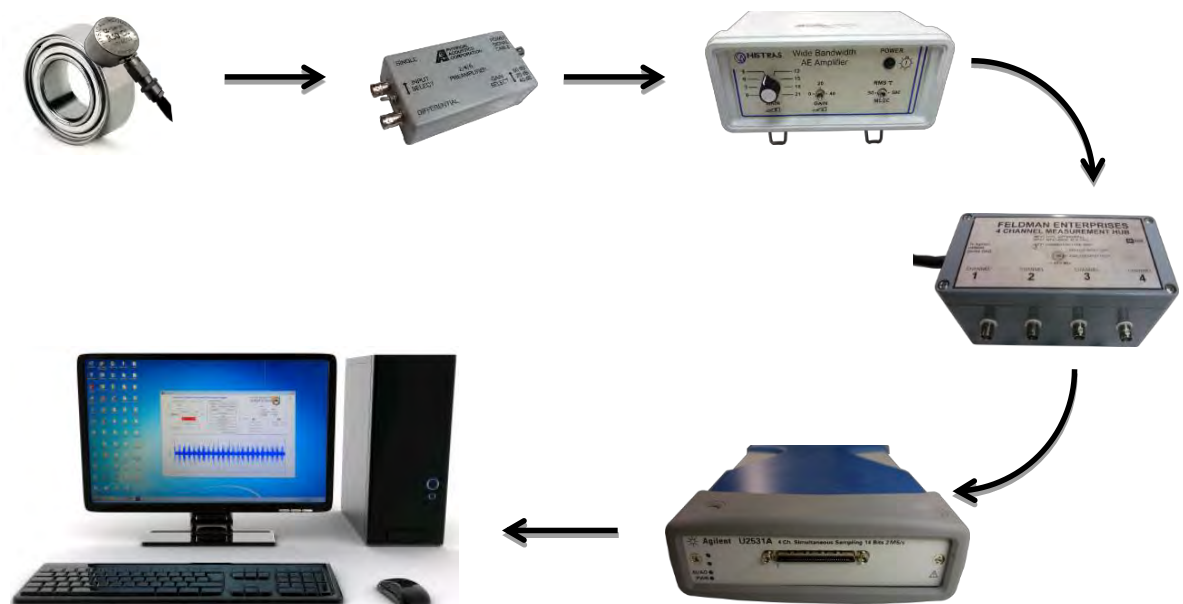


Figure 5.3: Bearing sensor test set-up

of interest. This is because the acoustic emission and vibration signals travel through medium and any discontinuity, such as joints, will attenuate and affect the signal reaching the sensors.

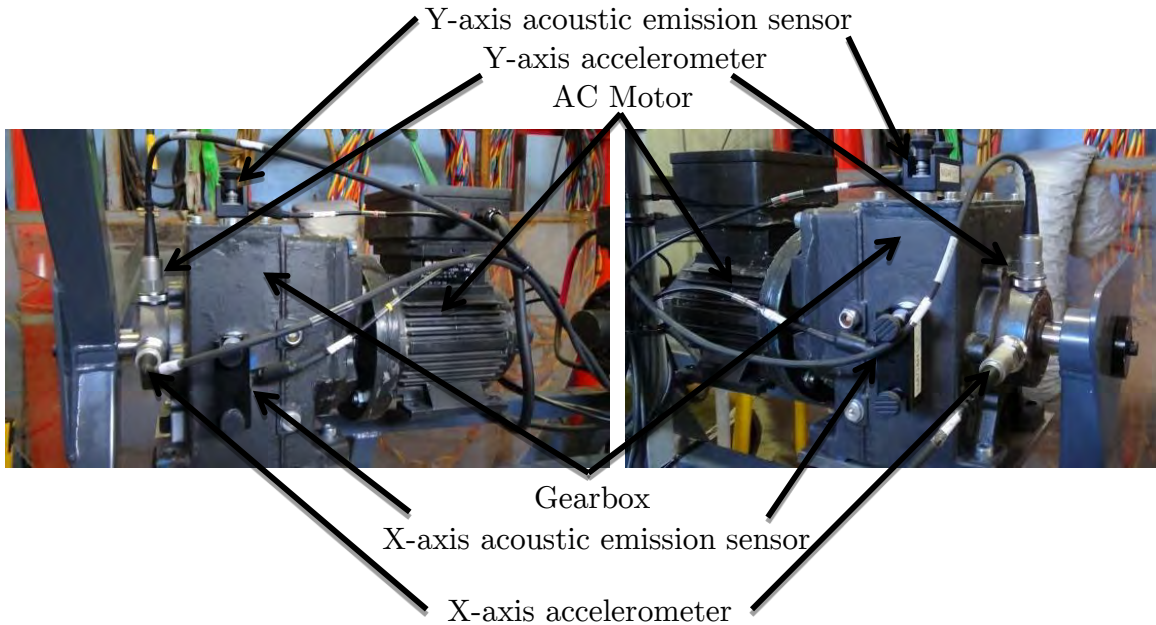


Figure 5.4: Industrial test-rig developed by TWI and University of Brunel to measure tidal turbine gearbox defect (Photographs are courtesy of TWI)

The gearbox used for the test was a 3-stage step down helical parallel axis, gear train with a ratio of approximately 1:69 as it is illustrated in figure figure 5.5

For submerged condition the two acoustic emission sensors VS900RIC procured from Vallen System GmbH with a range between 100 KHz to 1 MHz were mounted on the gearbox. For vibration, AC 150-2C accelerometers procured from Connection Technology Centre Inc were used. This sensor has a nominal operating frequency range of 1Hz to 10 kHz. The data collected from this test-rig has been used to analyse faults in the gearbox.

However, for the dry condition different sets of sensors have been use. Four Physical Acoustic Corporation R50 α sensors with a peak sensitivity of -62dB and operation frequency of 100 - 700kHz for acoustic emission measurement and two high-frequency 712F accelerometer by Wilcoxon Corporation with a nominal range of 3 Hz to 25 KHz used for vibration measurements. The amplifier and connections were the same with those used

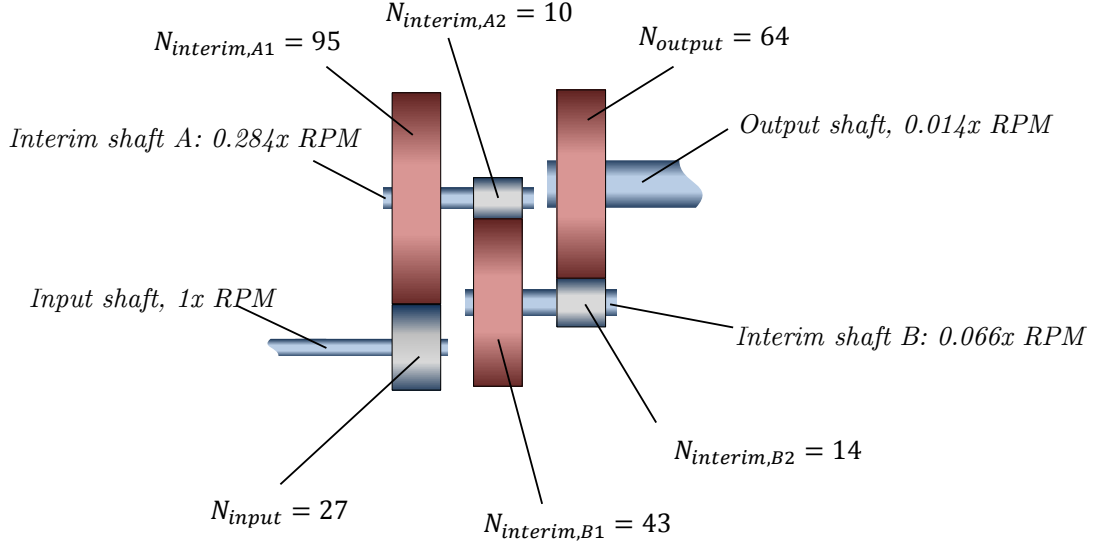


Figure 5.5: Schematic diagram of 3 stage gear train used in tidal turbine industrial test rig

for bearing measurements.

5.3 Sensor validation

After connecting the sensors and powering up the equipment, the first test is to evaluate the setup. This is done by producing a signal using a Hsu-Nielsen source (pencil-tip-break) as reference. This test, as it is illustrated in figure 5.6 produces a sharp, short and broadband acoustic pulse visible to the acoustic emission sensor. One of the advantages of this test is its simplicity and repeatability within an acceptable error range. At the first instance, the device under test which in this case is a bearing is firmly connected to the testing-rig while the mechanical driver (i.e. DC motor) is switched off. The driver has to remain off during the test and care has to be taken to prevent any unnecessary noise. Next, a pencil tip with specific length and an appropriate chamfer based on the pencil angle as shown in figure 5.6 placed on the bearing and pressed down firmly until it breaks. Extra precaution has to be taken so the tip of the steel collect does not touch the bearing after breakage of the lead. This procedure is done while the data acquisition unit is recording the sensor output.

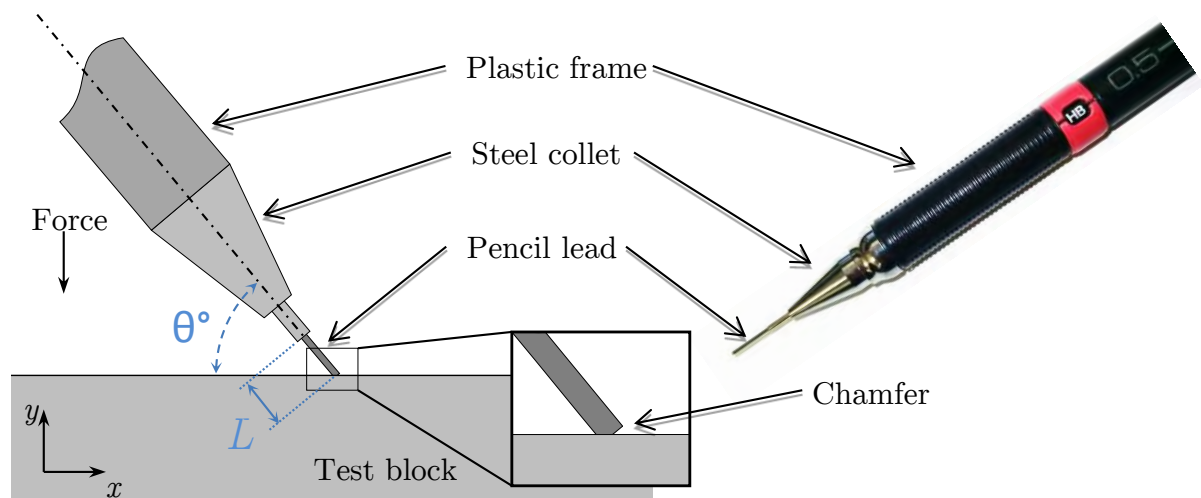


Figure 5.6: Hsu-Nielsen pencil break diagram

In the next step, the acquired data is viewed on the computer to verify the presence of the signal that was produced in the recorded data. The signal has to be sharp and short as we expected. Figure 5.7 illustrates the raw signals recorded on the bearing for one of the trials that has been done.

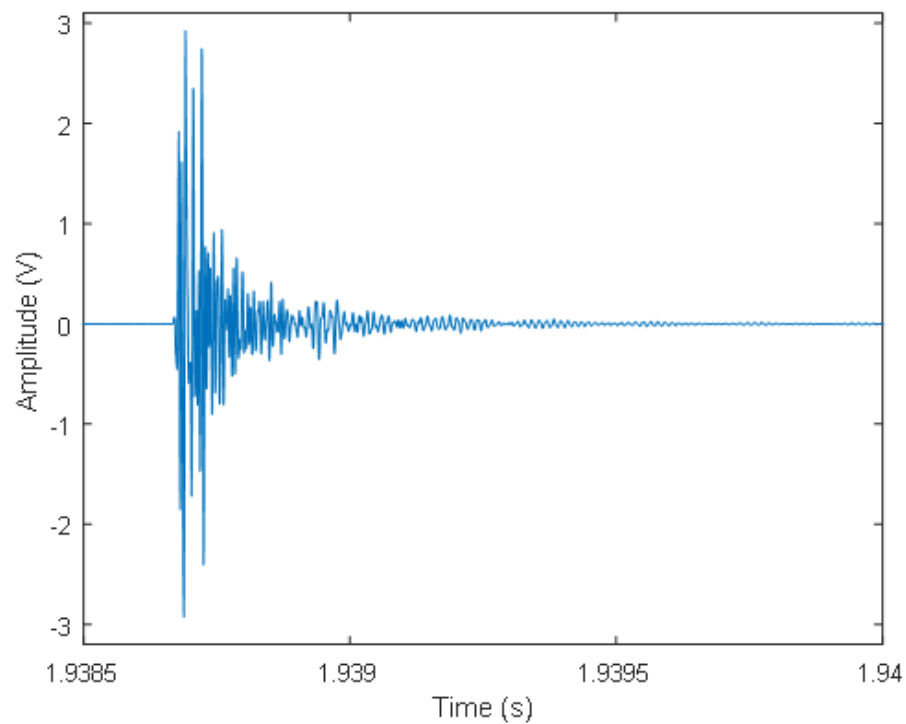


Figure 5.7: Raw data of pencil break

Finally, using the same technique, the gain of amplifiers has to be set to a proper value. This is a very important step to be done before recording the experimental data to prevent data saturation due to high gain. Similarly, small gain in the amplification will cause the signal to be masked by noise. The figure 5.8 illustrate the clipping effect at occurring at ± 10 volts caused by over amplification of the signal coming from the sensor.

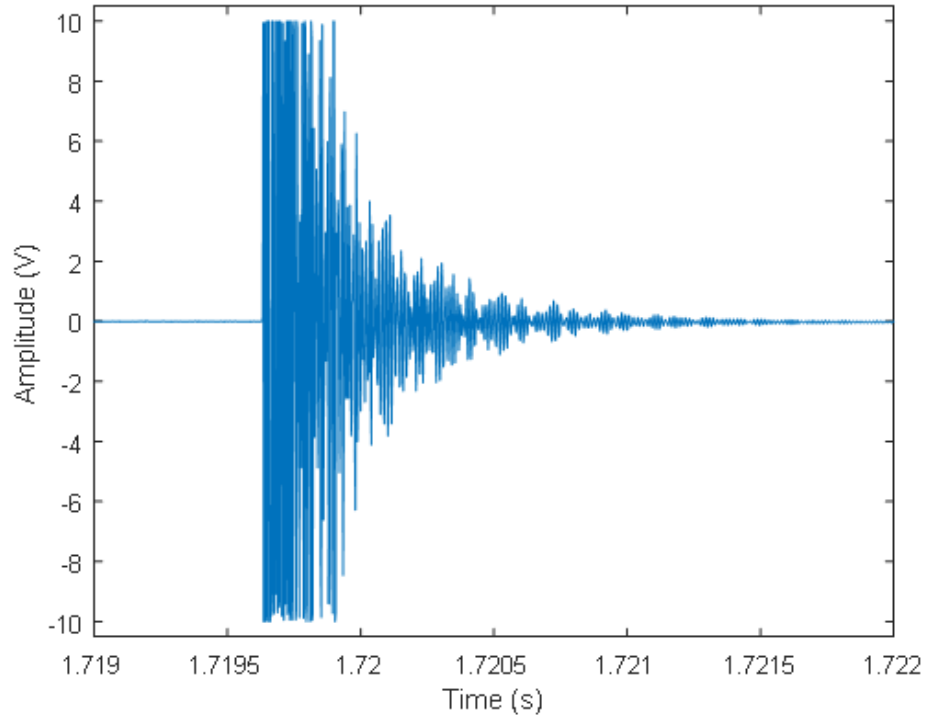


Figure 5.8: Saturated data of pencil break

5.4 Testing conditions

5.4.1 Bearing defects

Various induced conditions have been tested and the data were recorded for further data analysis. These were including different physical defects such as damaged roller inside the bearing as shown in figure 5.9. In each condition the data from both acoustic emission sensors and vibration sensors were recorded for several different speeds and applied loads.

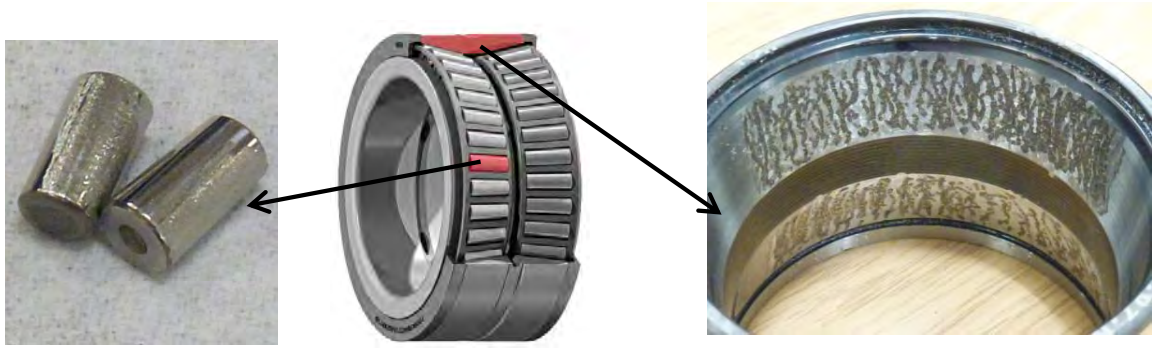


Figure 5.9: Double row tapered roller bearing, roller (left), outer race defect (right)

The investigation on the bearings defect was done with different types of physical damage as listed in Table 5.1 . The faulty bearings were provided by industry and the defects were induced to the bearing by the industry itself.

5.4.2 Gearbox

The gearbox condition was tested using a special tank facility at TWI in Middlesbrough using two different gearboxes. One refurbished gearbox known as healthy and one faulty gearbox. The tests were done both out of water and submerged inside the tank. Several gearbox fault conditions were induced and tested as individual or simultaneous. These were imbalanced gear i.e. bent shaft, gear tooth damage, impact and various combination of these.

The speed used for the test was chosen to be up to a maximum of 11 rpm going to the blades, with consideration of health and safety. This means a speed of about 750 rpm at the input shaft of the gearbox i.e. the speed of AC motor.

5.5 Results and discussions

5.5.1 Acoustic emission analysis of bearing

Originally, a healthy bearing was placed in the test rig for analysis and the data was recorded for various speed and loads. This data was used as a reference data for analysis

Table 5.1: Different types of physical damages induced to the outer race and roller of the bearing.

Bearing ID	Defect type	Details	Photo
ROLL1	Roller, minor	Minor damage to one of the rollers on each of the two racers. This was done by roughening the surface of the roller using electrical discharge engraver. The length of the induced fault was 10% of the circumference of the racers.	
ROLL2	Roller, moderate	Similar to ROLL1 condition above, but with deeper and larger damaged area. This is done using a small rotary grinder. The length of the damaged area is 50% of the circumference of the roller.	
RACE1	Racer, minor	Minor damage to the both racers of the bearing. This was done by roughening the surface of the racers using electrical discharge engraver. The length of the induced fault was 1.7% of the circumference of the racers.	
RACE2	Racer, moderate	Similar to RACE1 condition above, but with deeper and larger damaged area. This is done using a small rotary grinder. The length of the damaged area is 2.9% of the circumference of the racers.	
RACE3	Racer, major	Large ground and roughened fault on both racers induced by small cutting wheel and engraver. The length of the damaged area is 6.6% of the circumference of the racers.	
RACE4	Racer, significant	Significant damage to both racers induced by small cutting wheel and engraver. The length of the damaged area is 35% of the circumference of the racers.	

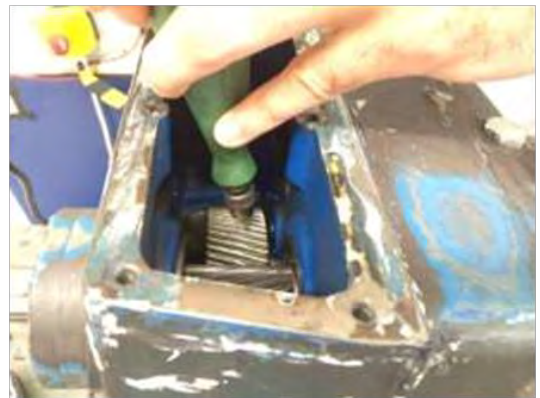


Figure 5.10: Inducing small chips on the gear teeth.

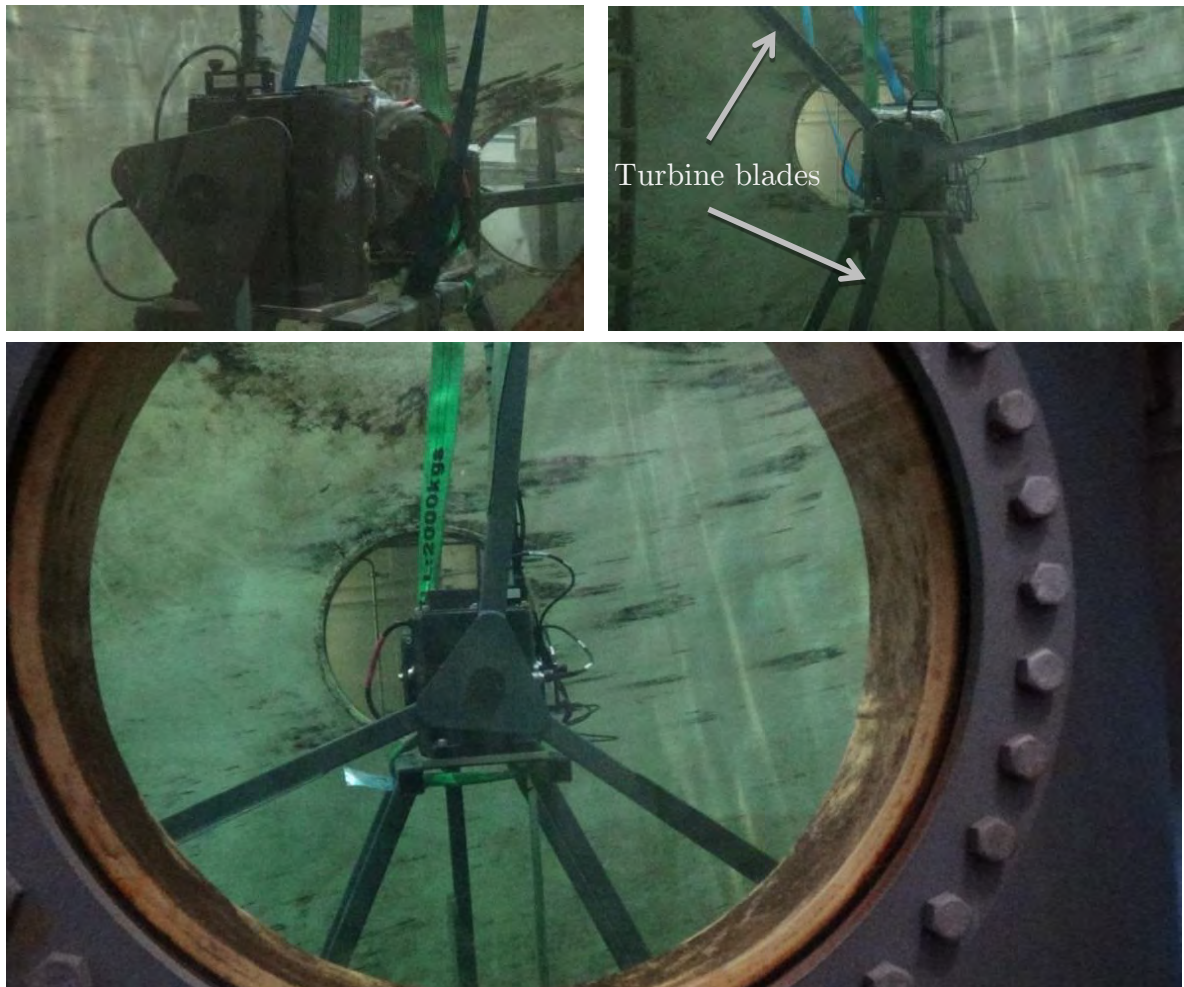


Figure 5.11: The Industrial test-rig shown in figure 5.4 during submerged tests (Photographs are courtesy of TWI).

of different defects and comparison purposes.

The physical damage described in Table 5.1 can be divided into two main categories; roller and race defects. Although these defects are linked and in reality, one can cause damage to the other, here they will be studied separately and their features will be shown using the techniques described in Chapter 4. The effectiveness of each technique to detect a particular fault will be discussed.

In general, it is expected that a healthy bearing runs smoothly and does not produce much vibration. However, when the surfaces of building components of the bearing degrade and deteriorate, they will become rough. Therefore, it is expected that moving surfaces produce some vibration due to the touching tough surfaces. Depending on the speed and the size of bearing this vibration can varies and it can be influenced by the amount of load (weight) applied on the bearing as well.

This suggests that although a prior knowledge is required to seek the signature of the fault, it should be possible to identify a faulty bearing without any prior knowledge about the bearing. Figure 5.12 confirms this claim as the faulty bearings shows noticeable variation in the produced acoustic signal, both in amplitude and the phase without any processing. The observed variation in both phase and the amplitude suggest that, both time and frequency signal processing techniques should be able to highlight and distinguish the defect.

This observation can be further analysed using frequency techniques such as FFT and HFRT. Decomposing the recorded signals using FFT analysis shows a significant raise in the frequency power. This is shown in figure 5.13. Due to the operating frequency range of the sensor which was used to record the data, the frequencies below 100 kHz are not of interest and the higher frequencies i.e. 100 kHz to 200 kHz are used to identify the faulty bearing. As it is shown in figure 5.13, faulty bearing has unique frequency characteristics and resonant peaks such as the sharp peak at around 165 kHz. Further prediction can be done by seeking frequencies calculated using Table 3.5.

Further analysis of the bearings showed that changing the load on either healthy or

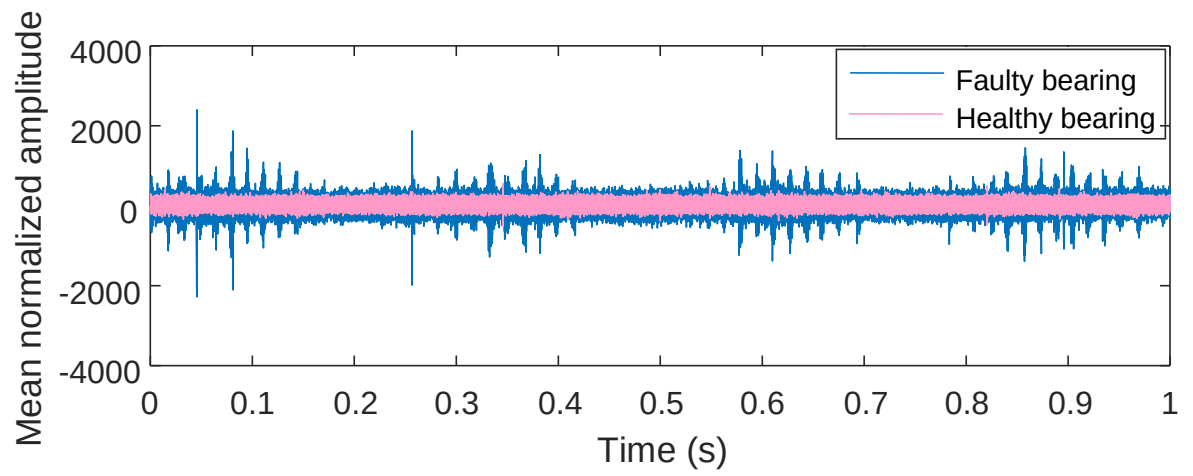


Figure 5.12: Comparison between raw acoustic signals recorded from a healthy bearing and a defective bearing with minor defects.

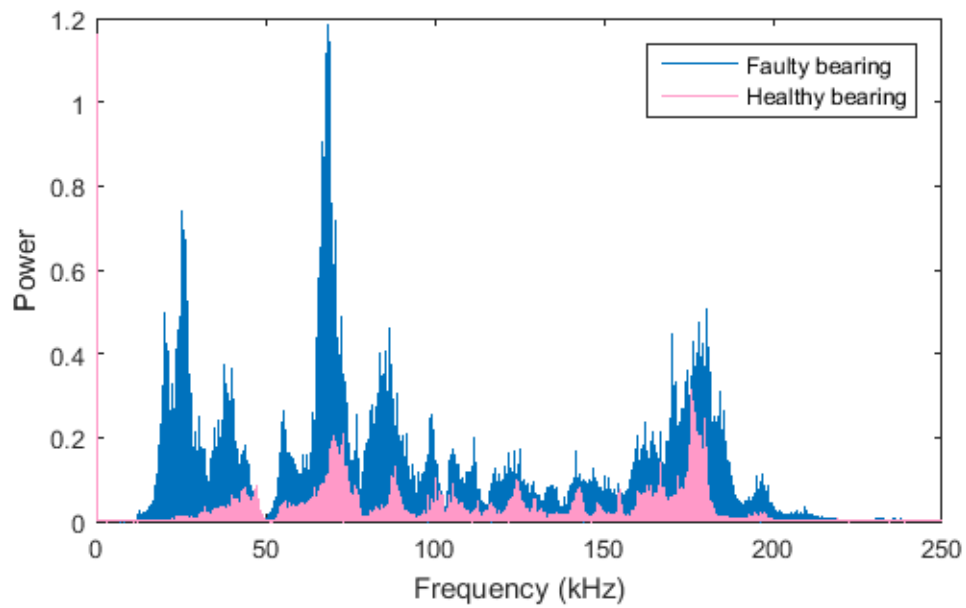


Figure 5.13: Fast Fourier transform of minor defected bearing.

faulty bearing is not visible in time domain. However, frequency analysis shows rather interesting result. Increasing the load on healthy bearings will increase the power of frequencies while this has opposite effect on faulty bearings. One possible reason could be that the load on the bearing causes the vibrations due to the rough surface of the components damp quickly. One example of this effect is presented in Figure 5.14.

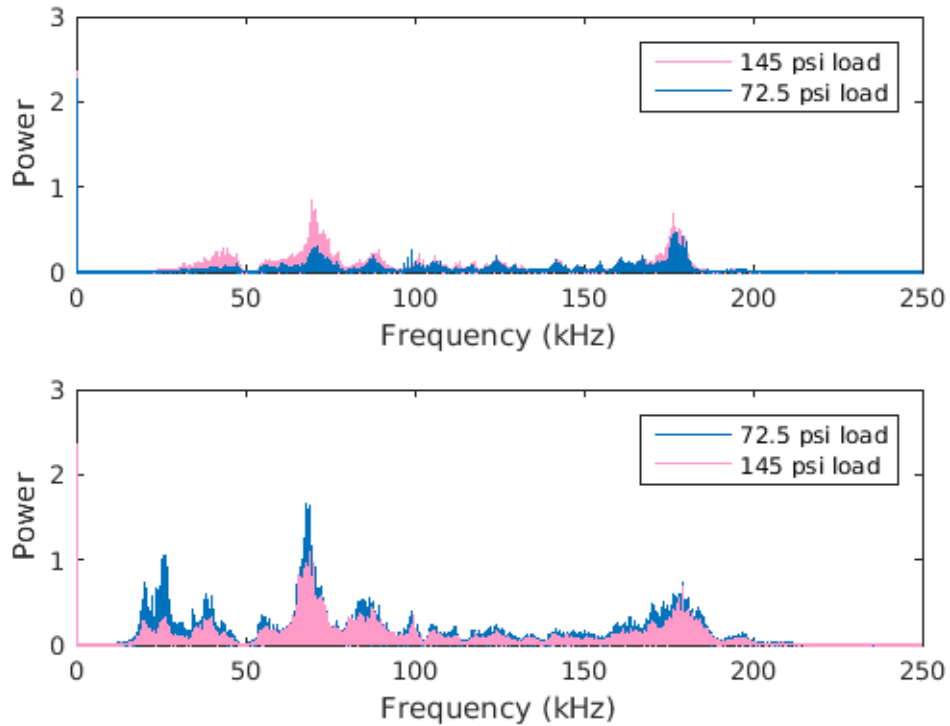


Figure 5.14: The effect of increasing load on healthy bearing (Top) and defective bearing (Bottom).

Further analysis looked into the effect of speed on the defective bearings. The bearings were held in place with a constant load of 72.5 psi (5 Bar) and the rotation speed was increased from 100RPM to 700RPM with 100RPM stepping. By increasing the speed in both healthy and faulty bearing, a significant rise in the signal amplitude is observable. Furthermore, normalising the signal to the mean does not help and no specific feature is observable in the time signal. Taking the FFT of the signal, however, shows noticeable changes in the frequency spectrum. As was discussed earlier, the fault in the bearing increases the lower frequencies and it is also evident that it has a wider spectrum at

higher frequencies. This is shown in the top panel of figure 5.15 for 100RPM. Increasing the speed, hardly changes the spectrum of the healthy bearing while it highly affect the faulty bearing and cause a big rise across the whole spectrum. This can be explained by the increasing of the instability of the faulty bearing at high speed. The bottom panel in figure 5.15 shows this significant rise across the spectrum using logarithmic scale. It also worth mentioning that the visible peaks at 100 kHz are very likely to be the interference from LORAN-C signal that is induced on cables during recording. LORAN-C is the low frequency radio navigation system broadcasting at 100 kHz long range which was primarily targeted for military uses.

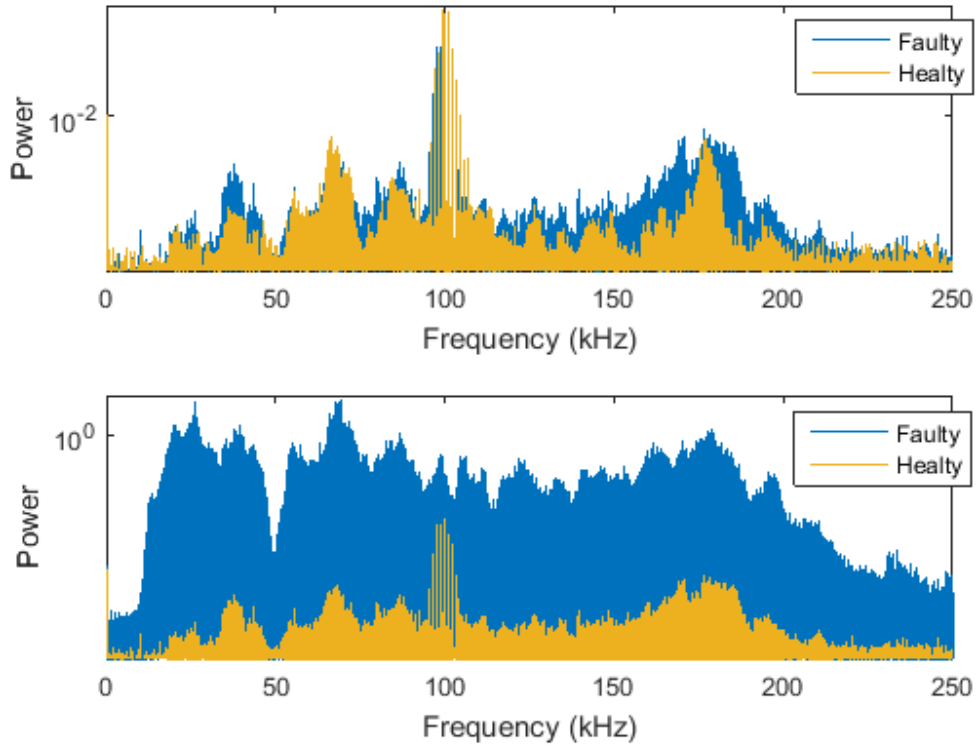


Figure 5.15: FFT analysis of a healthy and a minor defective bearing with 100rpm (top) and 700rpm (bottom). The power is represented in logarithmic scale.

Another noticeable drop in all the frequency spectrums at around 50 kHz is due to the sensor specification. The acoustic emission sensor used to record the data was calibrated based on ASTM industrial standard number E976 for acoustic emission sensors and is heavily attenuated at 50 kHz with a response of -100dB. This makes the sensor

not sensitive at that frequency and it is clearly visible in all the frequency spectrums. Figure 5.16 shows the frequency response of the used sensor. To normalise the sensor response, one would obtain the response gain difference from an arbitrarily set unity response and normalise the result of FFT analysis to the unity response gain calculated for each frequency.

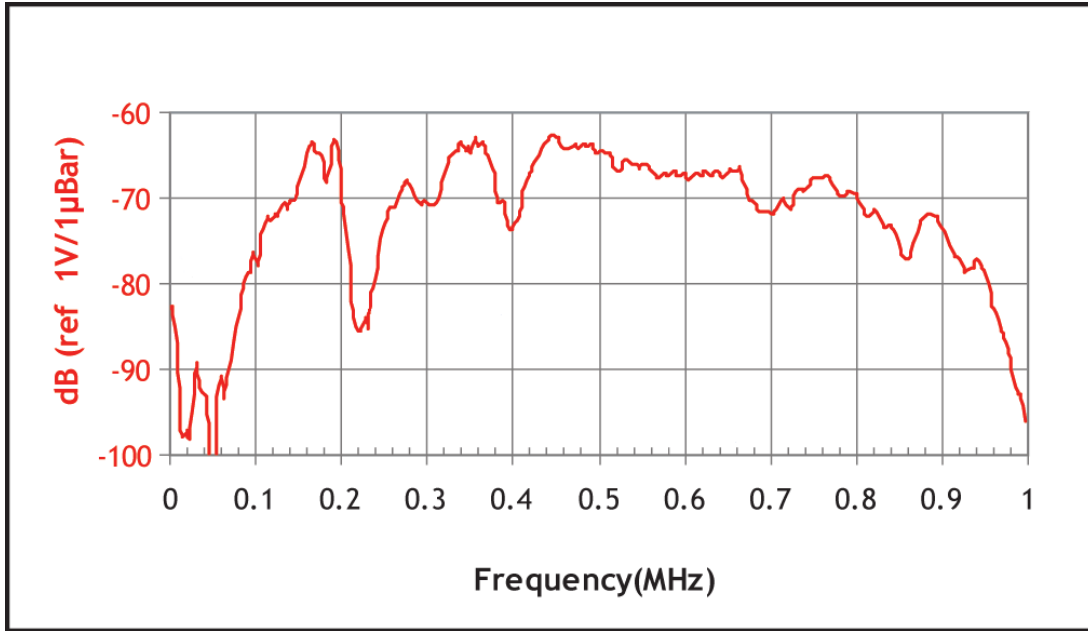


Figure 5.16: The calibration response of the R50 α sensor, calibrated based on ASTM E976 industrial standard.

Additional analysis carried out on the signals included comparison between different types of faults as was described in Table 5.1. As it is observed in figure 5.17, the faulty rollers, with either minor or moderate damage, cause a sharp peak at around 68 kHz and have a much wider spectrum. The faulty bearings (rollers) have a much richer spectrum above 200 kHz and below 25 kHz compared to the healthy bearing (rollers). This can be further analysed using Cepstrum analysis above 200 kHz as it is visible in the bottom panel of the figure 5.17 using logarithmic scale. The spectrum below 25 kHz which is also very informative is recommended to be analysed from the data recorded using vibration sensors as these sensors are sensitive to the low frequencies below 20 kHz.

Figure 5.18 compares the spectrum of various damages on the bearing racers with healthy bearing. The data along the X-axis between different faults is interpolated using

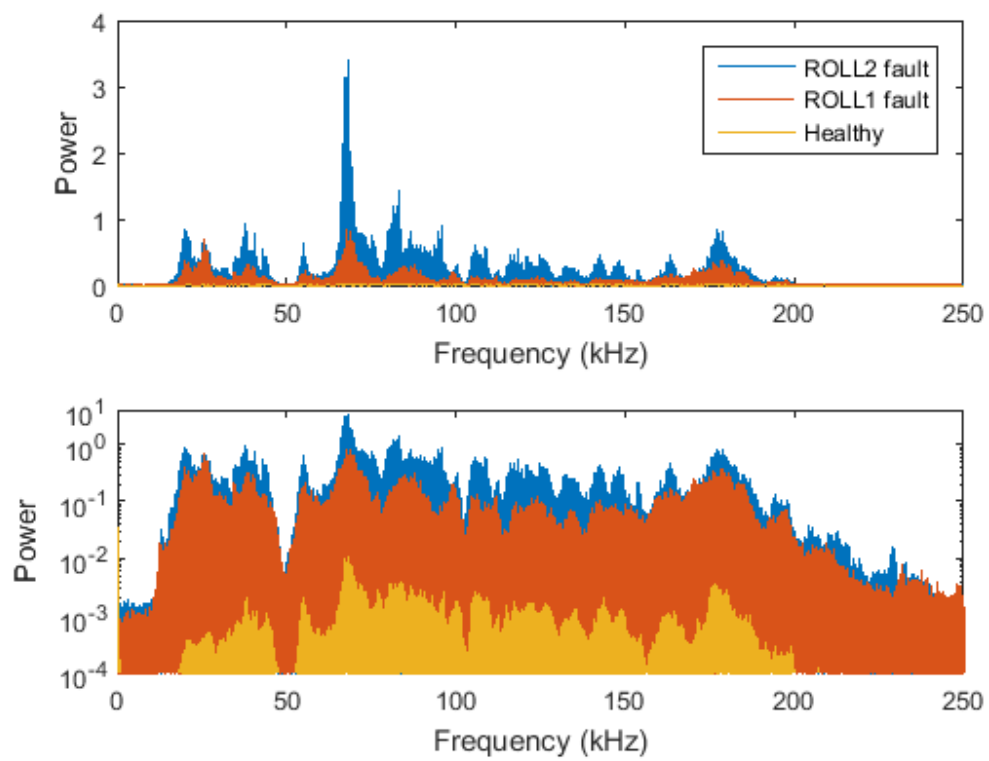


Figure 5.17: Comparison between healthy and faulty bearings with the fault induced on the rollers. Same data is represented in both panels with linear amplitude (top) and logarithmic amplitude (bottom).

cubic 2-dimensional interpolation technique. It is clearly visible from the figure that all the faulty bearings have low frequency vibrations below 40 kHz. Furthermore, there are certain frequencies that are only present in the faulty bearings such as 100 kHz or between 150 and 160 kHz. The peaks in the spectrum above 175 kHz also exist in all the faulty bearings while this range of spectrum is clean for the healthy bearing.

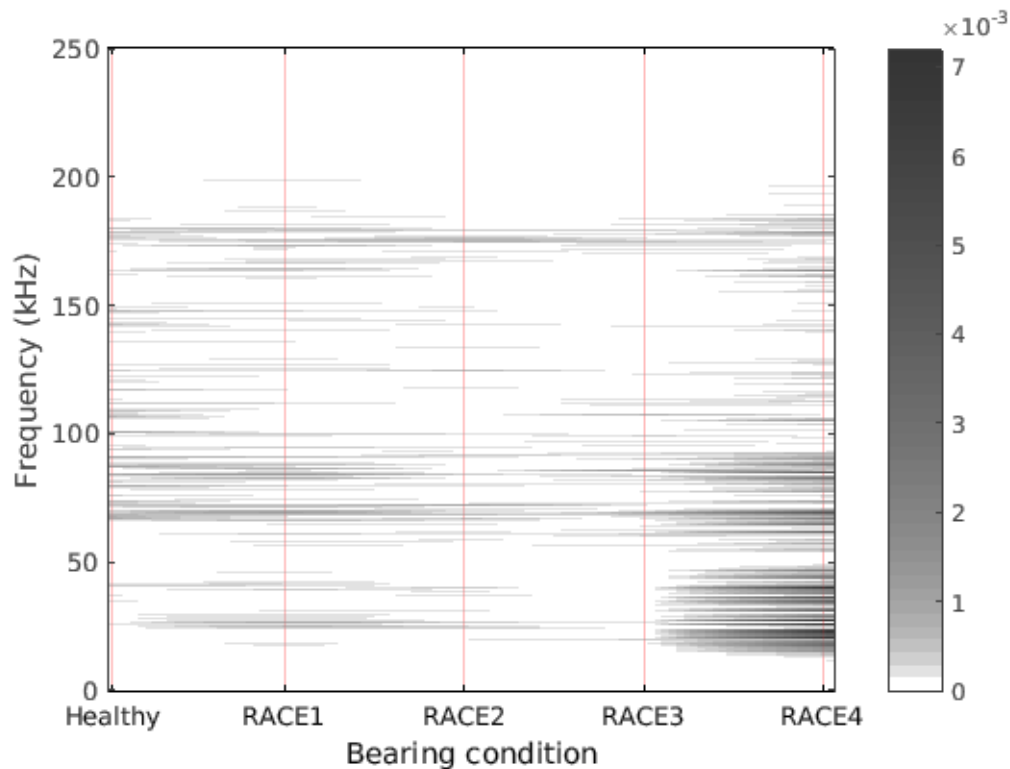


Figure 5.18: Comparison of spectrum analysis between healthy and faulty bearings with various faults induced in the outer racers of the bearings. The color scale representing the spectrum power.

As it was shown each defect on the bearing has either time or frequency (spectrum) unique features that are identifiable. It is possible to distinguish between different faults using acoustic emission signals. Using a simple threshold indication in the time domain (e.g. RMS value) or frequency domain (e.g. isolating a frequency band using HFRT) these faults can easily be distinguished and identified in a recorded signal. Next, these defects will be studied using vibration (below 25 kHz) to identify the suitability of vibration signal to identify and distinguish various faults in bearing.

5.5.2 Vibration analysis of bearing

Most of the tidal and wind turbines rotate at relatively slow speed [149] and, as it was mentioned earlier the gearbox, has the role to speed up this slow speed to a faster rotational speed for the generator. However this speed does not exceed few hundreds of RPM. This means the frequency of the rotating gearbox would be of the order of few tens of Hz. This frequency is well in the range of vibration sensors that are typically sensitive to frequencies below 20 kHz.

As it was explained earlier using the physical dimensions of the bearing or gearbox it is possible to calculate the exact frequencies at which each component would be vibrating naturally. Consequently, any defect will affect those frequencies directly and are expected to be identifiable in the spectrum. In case of bearing these frequencies are the ones that have been listed in Table 3.5.

The physical parameters of the bearing that has been used for the experiment are listed in Table 5.2 and the characteristic frequencies were calculated using Table 3.5.

Table 5.2: Used bearing physical parameters.

Parameter	Symbol	Value
Pitch Diameter	Pd	42.5 mm
Ball(roller) Diameter	Bd	5.3 mm
Number of balls (rollers)	Nb	21
Contact angle	α	13.8°

The bearing was tested at various speeds and Table 5.3 provides the characteristic frequencies at 100 RPM and 700 RPM, corresponding to the results presented in this thesis, for convenience. However, it is possible to calculate these frequencies for any given speed using Table 3.5. The bearing physical parameters as listed in Table 5.2.

For a bearing with outer race damage it is expected to identify the BPFO frequency in the spectrum with side-bands at 1X (rotational speed of the shaft). This was investigated on the faulty bearing defined as Race 3 in Table 5.1 for speed of 100 RPM. The time signal

Table 5.3: Calculated parameters for the used bearing under the test at 100 RPM and 700 RPM speed.

Parameter	Value (Hz) at 100 RPM	Value (HZ) at 700 RPM
FTF	0.733	5.13
BPFO	15.38	107.68
BPFI	19.62	137.32
BSF	6.58	46.08
BPFI	19.62	137.32
Speed	1.67	11.67

of this faulty bearing is compared to a healthy bearing of the same kind has been shown figure 5.19 As it can be seen there are some low frequency vibrations visible at around 1.23 seconds on the top panel which is the faulty bearing. However, this is not easy to identify and more advanced processing such as envelope analysis or HFRT has to be carried out to highlight these small changes. Furthermore, the quantization error is clearly visible on both signals due to the very small amplitude of the sensor and low resolution of the recording equipment (ADC). This can be addressed by either using a higher resolution ADC or interpolate the signal using FFT zero padding or Spline interpolation.

Nevertheless, the frequency spectrum clearly shows these vibrations that are occurring at BPFO and its 1X side bands. Figure 5.20 presents the frequency spectrum of the faulty bearing race 3, with a sharp pick at 15.35 Hz and its two 1X side bands at 13.83 Hz and 17.07 Hz.

Looking at higher speed rotating bearing, the vibrations become even more visible with the faulty bearing. This makes it possible to detect the fault using time domain techniques such as moving RMS technique. Figure 5.21 compares the time series and moving RMS of a healthy signal and a defective signal at 700 RPM. As it can be seen in the figure, the fault on the race will cause significant sharp peaks and the moving RMS easily can identify the fault with a simple threshold.

Similar to slow moving bearing, it is expected to observe the fault vibration peaks in the spectrum of the signal. Fig 5-22 shows the spectrum of a bearing with damage

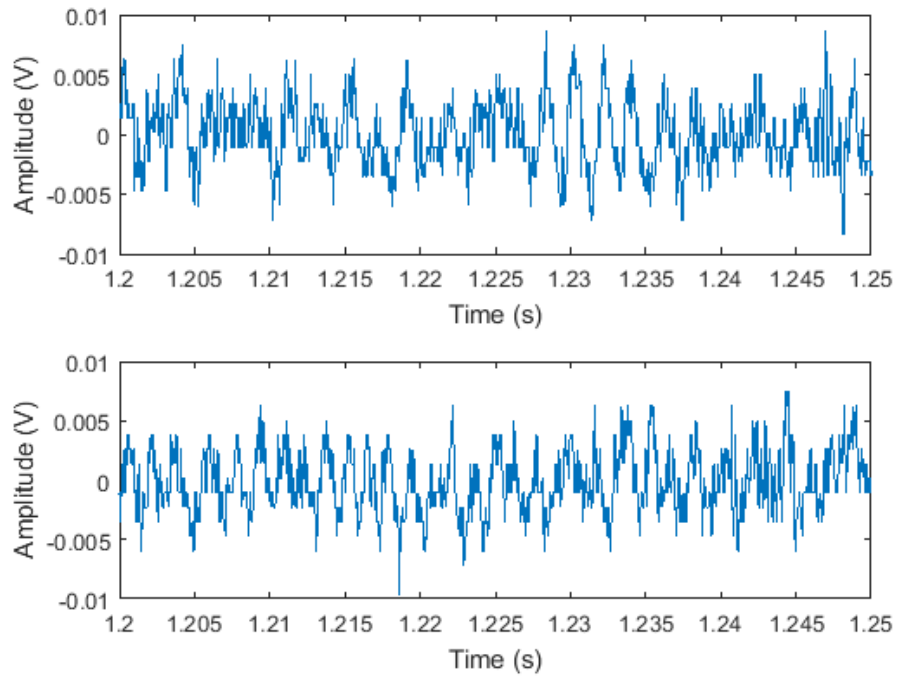


Figure 5.19: Comparison between time domain of the same kind bearing with race 3 induced fault on top panel and healthy bearing on the bottom panel.

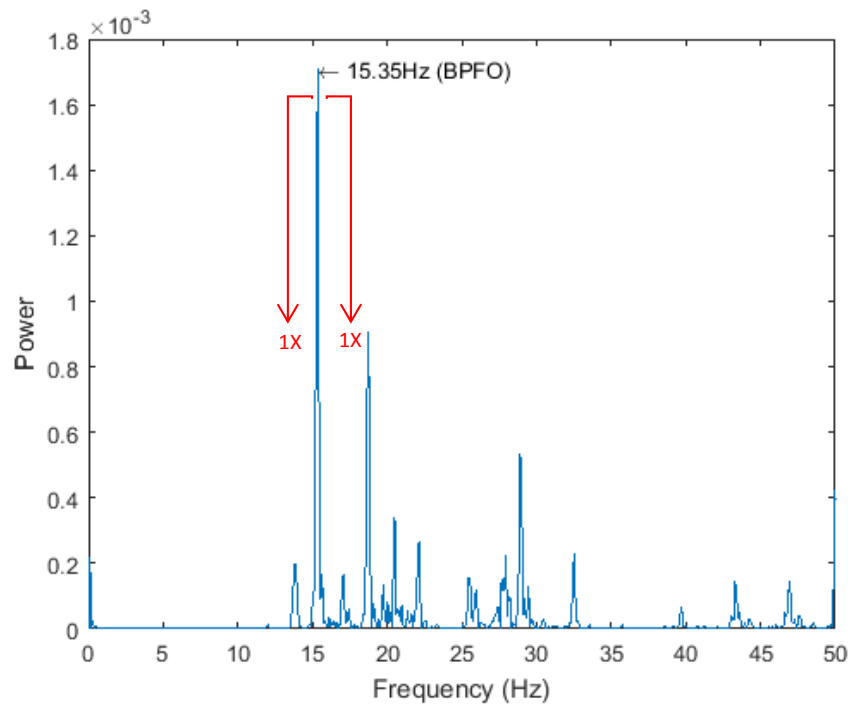


Figure 5.20: Frequency spectrum of a bearing with induced race 3 fault showing the BPFO and its two 1X side bands running at a speed of 100 RPM.

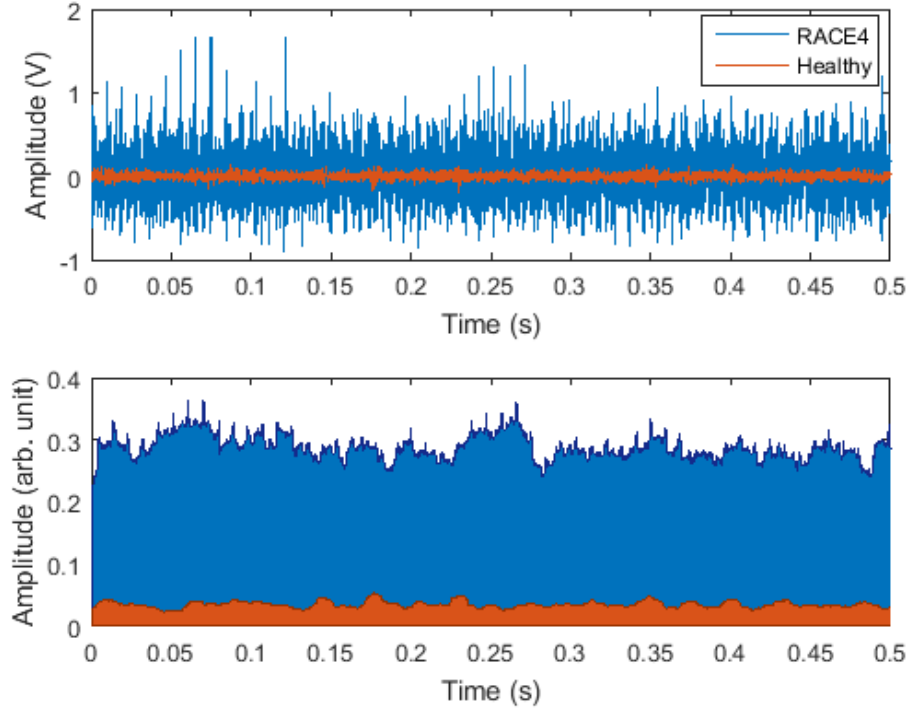


Figure 5.21: Time series of raw signal (top) belonging to a healthy and a defective bearing and moving RMS (bottom) of the same bearings with a windowing of $F_s/100$.

to the race (RACE4 condition) running at 700 RPM. There is a sharp peak at 1X and its harmonic 2X as well as sharp peaks at outer race fault frequency and its side bands ($\text{BPFO} \pm 1X$).

Taking the spectrum of the signal on a short window of time allows instantaneous fault detection in time or degradation monitoring of the bearing over time instead of single shot spectrum. Figure 5.23 shows the change in the spectrum over half second window for a healthy bearing and a faulty bearing with RACE4 defect. The sharp harmonics in the spectrum of the faulty bearing makes it very noticeable in comparison with the healthy bearing with smooth spectrum.

This clearly shows that it is possible to identify the fault in the bearing using vibration technique very quickly with simple signal processing techniques. Being able to identify small defects in the bearing using simple and fast techniques without much computation, makes it possible to create reliable online and real-time monitoring systems with low cost

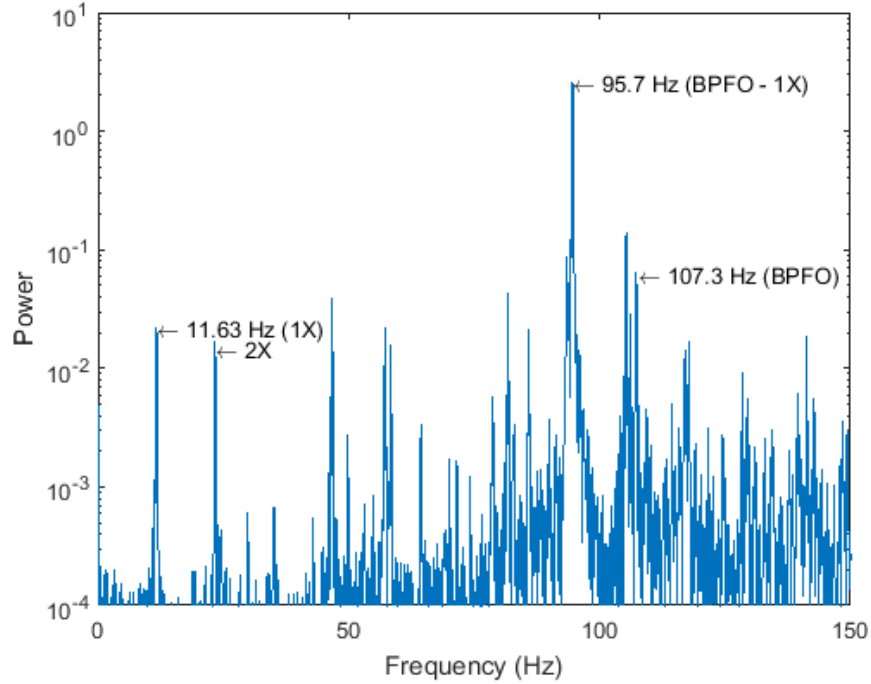


Figure 5.22: The spectrum of a bearing with RACE4 defect showing peaks at bearing characteristic frequencies for the outer race defect at 700 RPM. .

that is desirable for industries. However, in the cases involving a complex gearbox these simple techniques might not be able to identify the fault because of the contamination in the signal caused by noise generated by other components in the gearbox and the usage of more advanced techniques such as HFRT is inevitable.

5.5.3 Acoustic emission analysis of gearbox

As it was discussed earlier, the acoustic emission signal is much richer than the vibration signal and covers a wider range of frequencies. For simple systems such as isolated bearings or motors, calculating basic indicators of the acoustic emission signal such as signal spectral power and signal spikiness (i.e. kurtosis) would be sufficient to indicate the health of the system. However, as the complexity of the system increases, the requirement for further analysis of the signal becomes inevitable. In a complex system it is very beneficial to understand which part of the system is degraded or damaged.

The most common technique used to process acoustic emission signals is demodulation

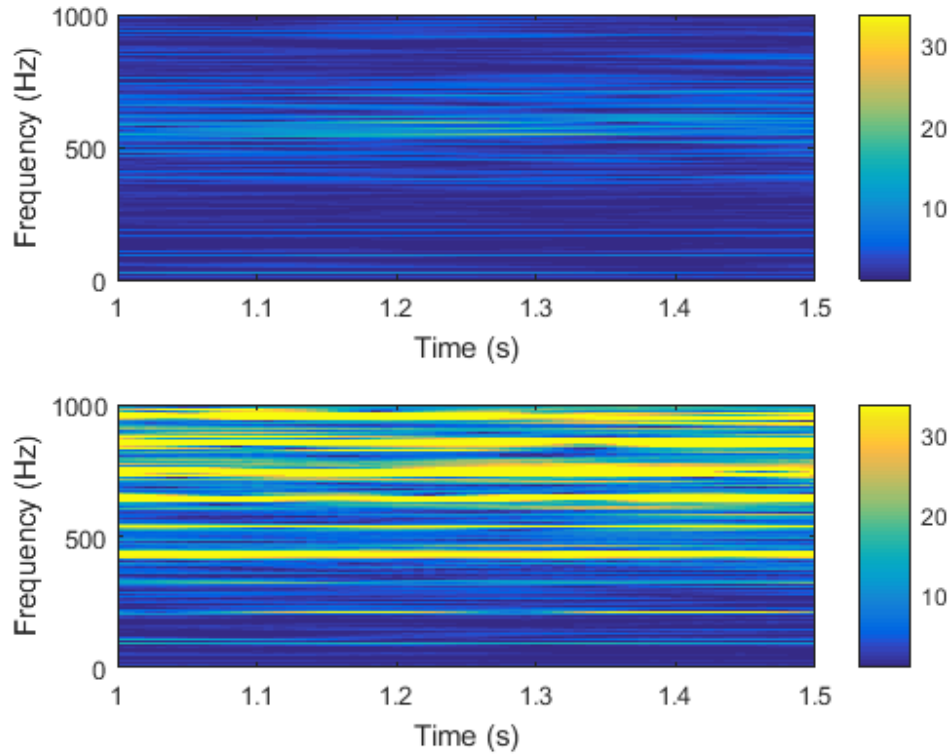


Figure 5.23: Short window spectrum of a healthy bearing (top) compared to a defective bearing with RACE4 defect (bottom) at 700 RPM. The colour scale indicates the level of power in the spectrum.

or envelope analysis. The demodulation technique is very useful for detecting rolling element failures in early stages of development when they are not yet detectable in the vibration spectrum or they are at very low frequency, i.e. $< 2\text{Hz}$.

A bearing vibrating at its natural frequency due to wear or pitting on its outer race will generate a time signal similar to figure 5.24 (top) with higher frequency representing the bearing natural vibration and spikes will be the result of rollers hitting the pitted area. Taking the Fourier Transform of this signal will highlight the dominating natural in the power spectrum as shown in figure 5.24 (bottom). By using the enveloping technique, the hidden features of the signal can be extracted. In this particular example discussed here-with, the extracted feature would be the ball pass frequency of outer race (BPFO). This can give an indication of bearing damage which may not be obvious using conventional spectral analysis as illustrated in figure 5.40.

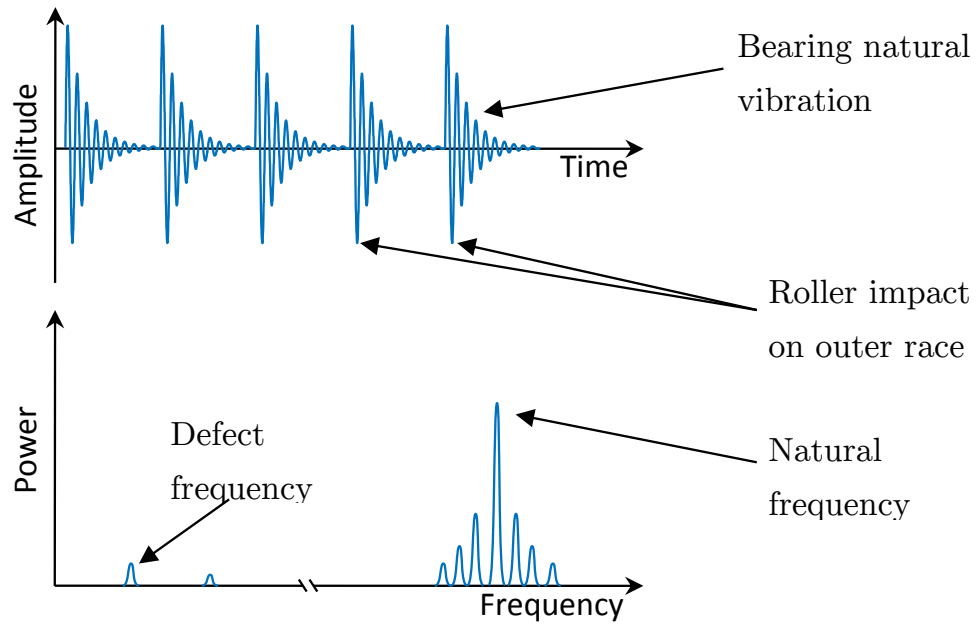


Figure 5.24: An example of defective bearing (outer race) vibration signal in time domain and corresponding FFT.

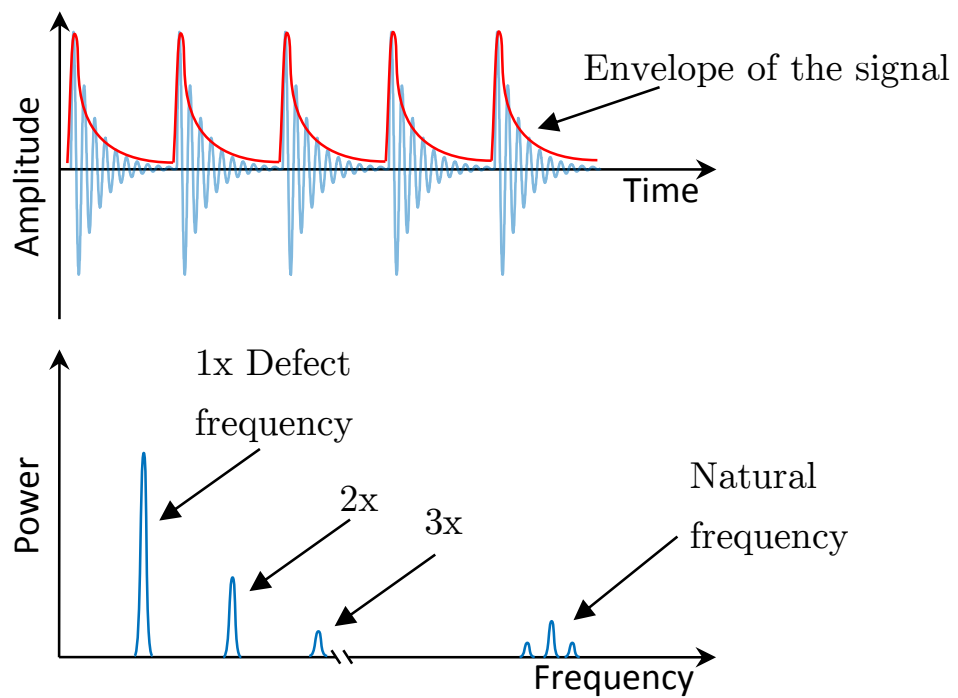


Figure 5.25: An example of signal envelope of vibration of a faulty bearing (outer race) in time domain and the corresponding FFT.

The enveloping technique can be very useful to detect a developing fault at its early stages and extract the frequencies of interest from a noisy signal. This technique can also help with very low frequency vibrations and detection of the faults located in low speed rotating shafts.

By having prior knowledge about the gearbox kinematics, it is possible to calculate the different frequencies corresponding to each of the gearbox components. For this particular test, the gearbox was driven at an approximate rotational speed of 750RPM. With the knowledge about the number of gears in each stage the gear feature frequencies have been calculated at 750RPM. The details are tabulated in table 5.4.

Table 5.4: Characteristic frequencies of utilised gearbox running at 750 RPM.

Feature	Natural Frequency		1 st Harmonic (Hz)	2 nd Harmonic (Hz)
	RPM	Hz		
Gearbox Input Shaft	750±50	12.5±0.83	25±1.66	37.5±2.49
1 st stage Gear Mesh	—	337.5±22.5	675±45	1012.5±67.5
Interim Shaft A	213.16±14.21	3.55±0.24	7.1±0.48	10.65±0.72
2 nd stage Gear Mesh	—	35.53±2.36	71.06±4.72	106.59±7.08
Interim Shaft B	49.57±3.31	0.83±0.05	1.66±0.1	2.49±0.15
3 rd stage Gear Mesh	—	11.57±0.77	23.14±1.54	34.71±2.31
Output Shaft	10.84±0.73	0.18±0.01	0.36±0.02	0.54±0.03
3 rd stage gear assembly phase frequency (GAPF)	—	5.78±0.39	11.56±0.78	17.34±1.17

The gearbox was initially tested in healthy condition with no induced damage and a balanced rotor load. The recorded acoustic signal and its corresponding FFT are presented in figure 5.26 and figure 5.27 respectively. As it can be seen in figure 5.27, the 3rd stage gear mesh phase assembly as well as the 3rd stage gear mesh is noticeable in the frequency domain. This is the high speed output stage where the blades are located. Further signal processing using the demodulation technique reveals periodicity of the signal at low frequency based on RMS analysis. Considering the FFT of the demodulated signal, it can be seen that three further peaks at 1, 2 and 2.5Hz have arisen. These peaks are

likely to arise from the bearings. The RMS signal and corresponding FFT are shown in figure 5.28 and figure 5.29 respectively.

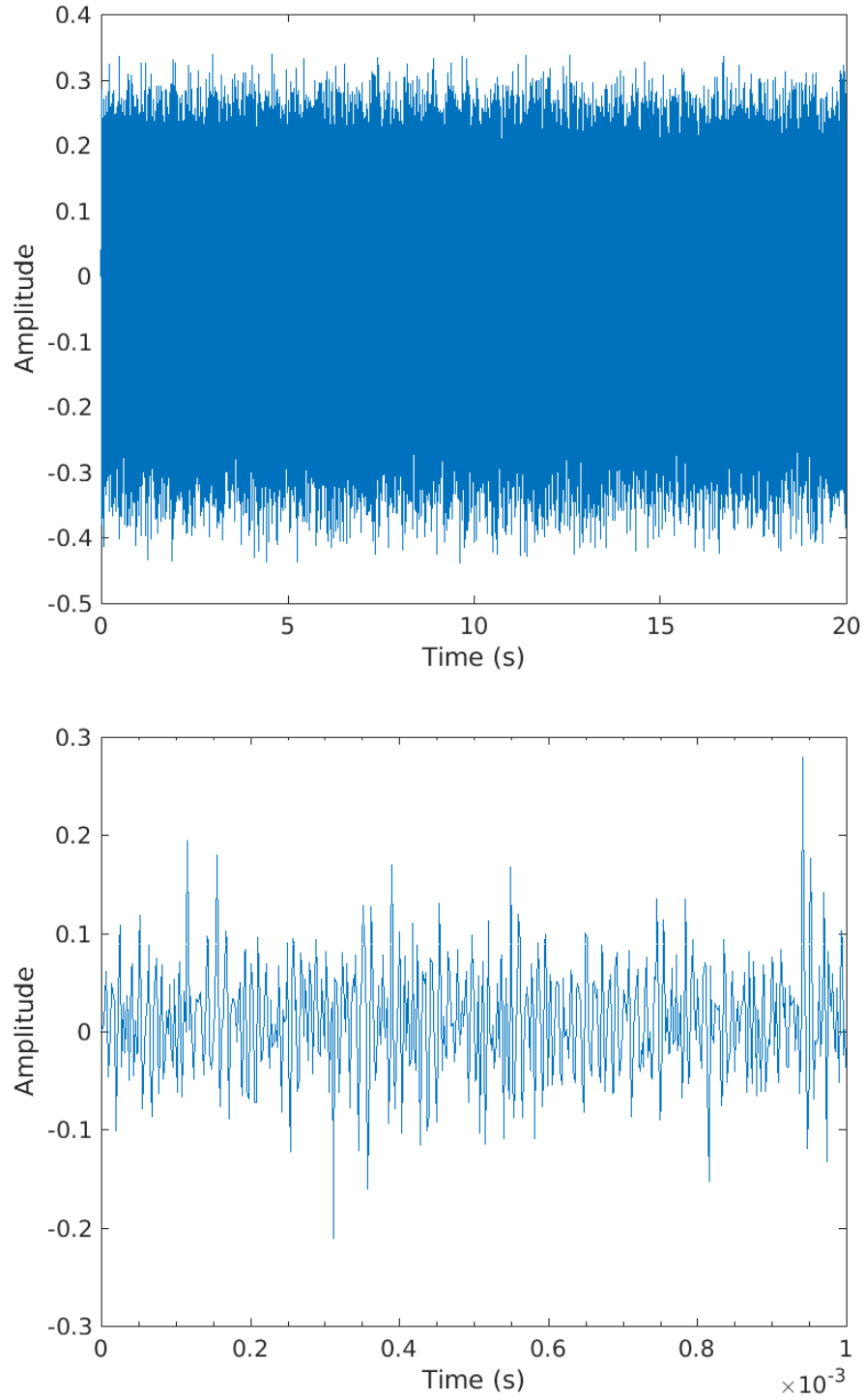


Figure 5.26: The acoustic emission signal of the tested gearbox under healthy condition showing the entire signal on top and zoomed on bottom.

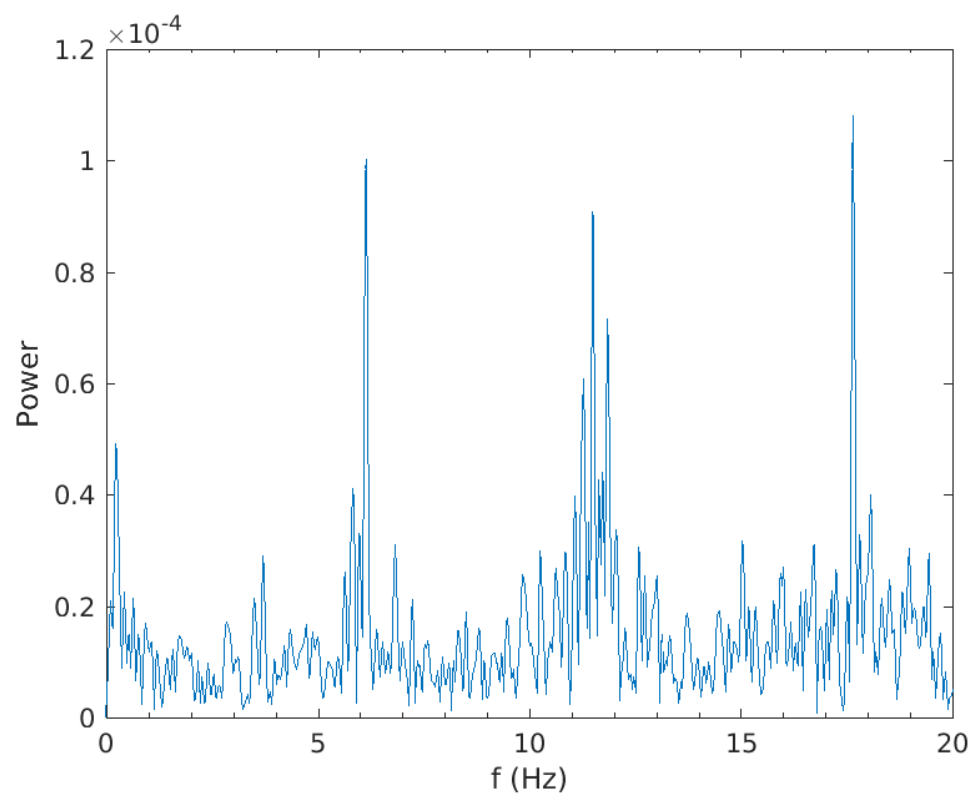


Figure 5.27: FFT of the tested gearbox under healthy condition calculated using Hanning window.

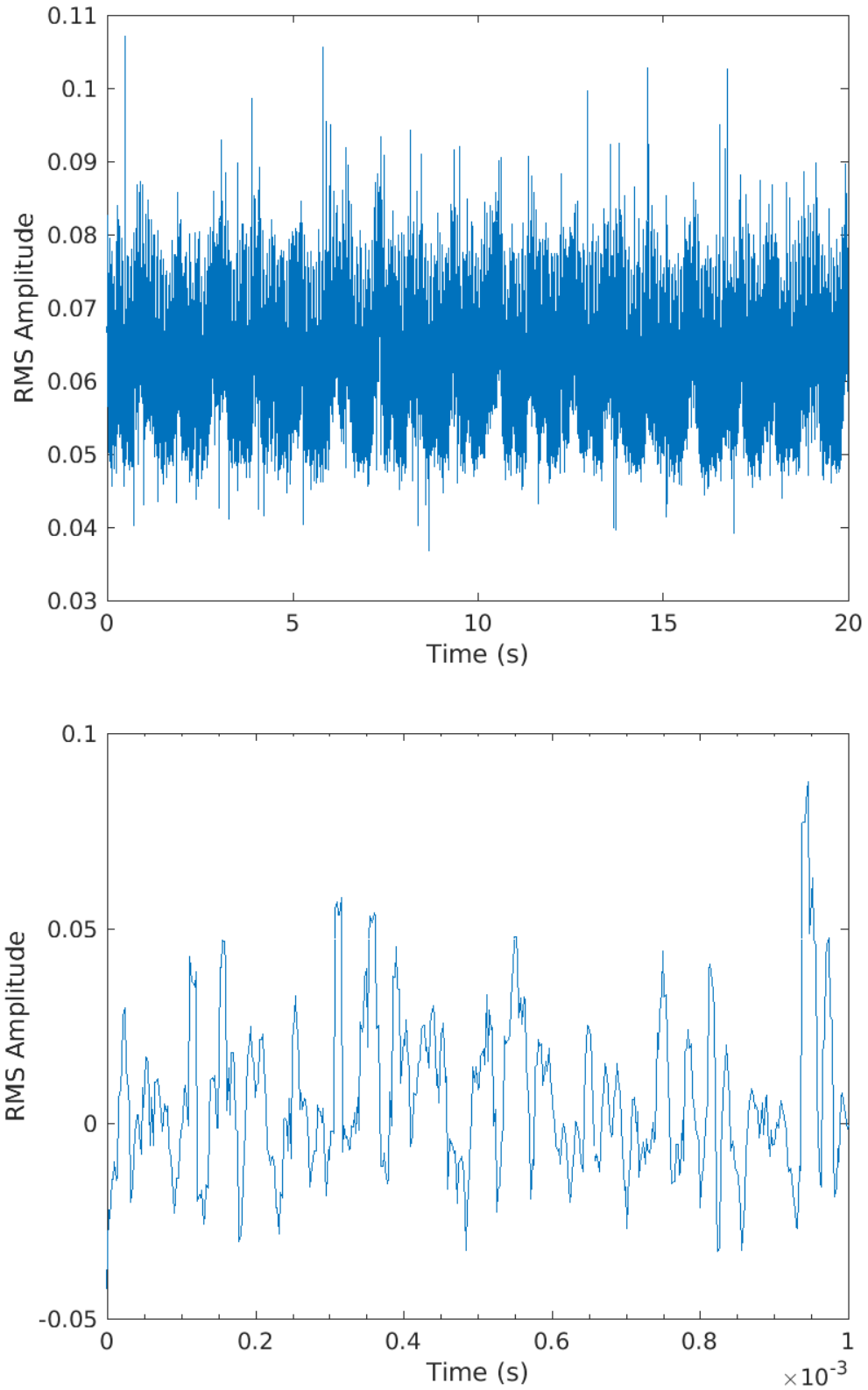


Figure 5.28: The demodulated signal using RMS analysis with a window size of 1ms (FS/1000) calculated from acoustic emission signal from healthy gearbox showing the entire signal on the top and zoomed on bottom (mean removed).

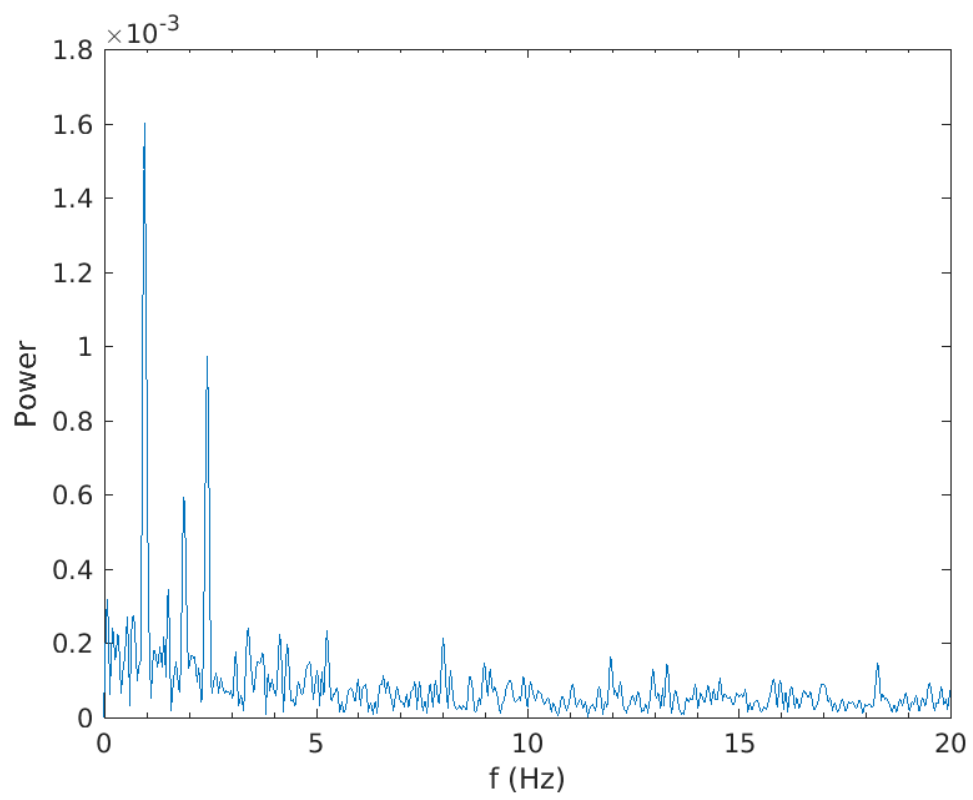


Figure 5.29: The calculated FFT of the demodulated signal from healthy gearbox calculated using Hanning window.

Next, the gearbox was evaluated under imbalance condition. A similar signal processing procedure as for the healthy condition was employed. The results of the analysis are presented in figure 5.30 to figure 5.33. Both time and frequency domain representations of the raw signal are very similar to the healthy condition. In particular the low frequency range of both signals are almost identical and not distinguishable even by pairwise residual difference calculation.

However, the envelope of the signal for the imbalance condition (figure 5.32) is very distinguishable from the envelope of the signal recorded in good condition (figure 5.28). Consequently, the FFT of the envelope showing several high amplitude peaks at very low frequency that were not present for the analysis under the healthy condition. Two of these peaks correspond to the output shaft (0.18Hz) and interim shaft driving the output shaft (0.83Hz). Usually, detecting the high amplitude first harmonic peak is a sign of misalignment. However, in this particular case this is caused by the effect of imbalance. This was only possible to detect using the enveloping or demodulation analysis approach.

In addition, the effect of impact on the rotor blades was investigated. This is very important since severe damage to the blades and subsequently other components of the turbine can be caused by impact events. Impacts on the rotor can result from a range of factors including debris carried by water streams or marine life.

Impact testing was carried out during the normal operation of the customised test rig tidal turbine by impacting one of the blades with a steel hammer while they were rotating at a fixed speed of around 11RPM. The hammer impact was very light and not damaging to verify if it will be captured using acoustic emission sensors and accelerometers mounted on the nacelle in the area of the gearbox. As it can be seen in figure 5.34, the impact events are clearly visible in the raw time signal recorded using the acoustic emission sensor. The calculated RMS value using 1ms window has been analysed. Figure 5.35 shows a stronger impact event on the blades. As it can be seen the amplitude of the peak is significantly higher than the light impact and easily identifiable.

Next, artificially induced gear teeth wear (figure 5.11) was investigated using various

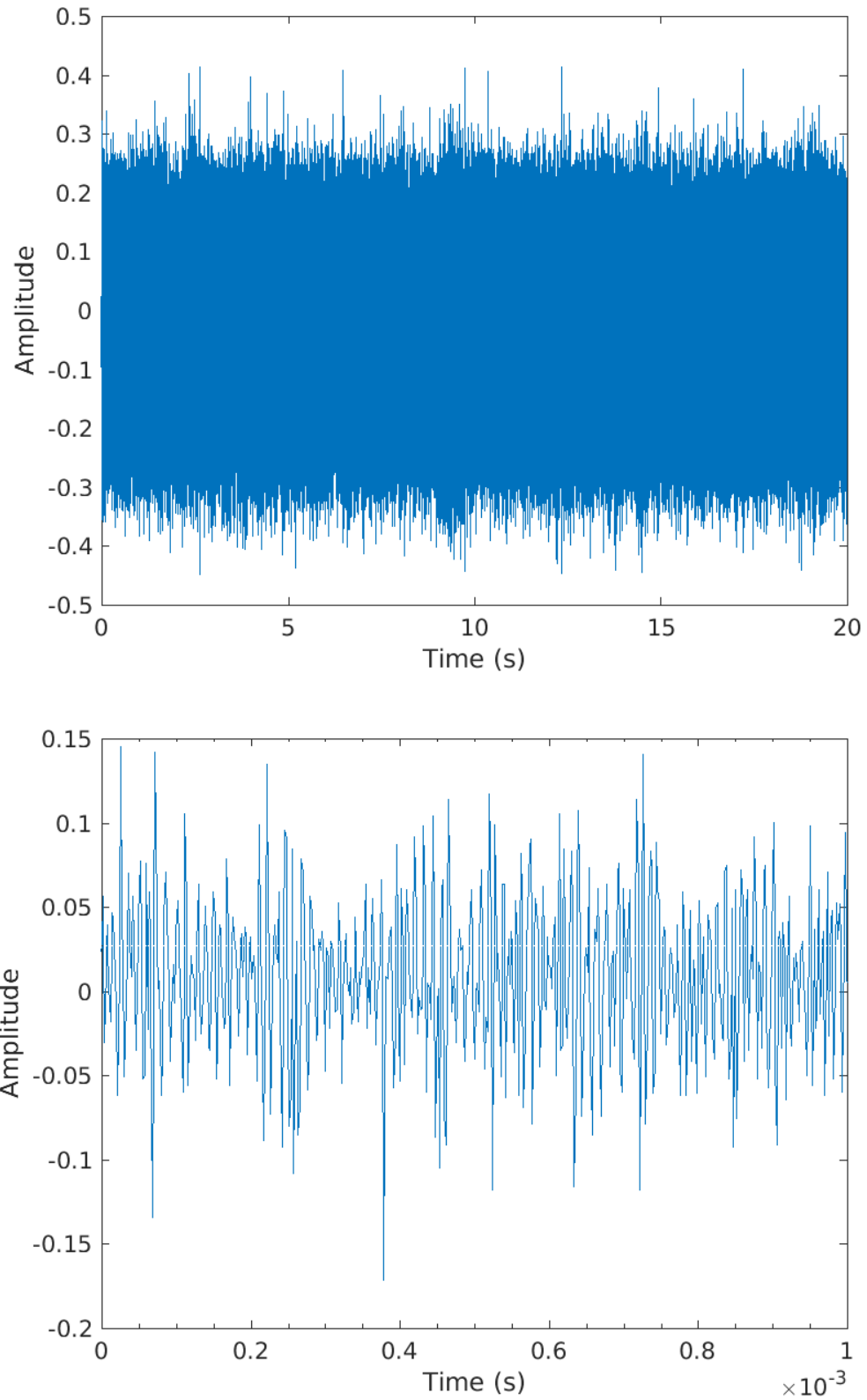


Figure 5.30: The acoustic emission signal of the gearbox with imbalanced condition showing the entire signal on top and zoomed in on bottom.

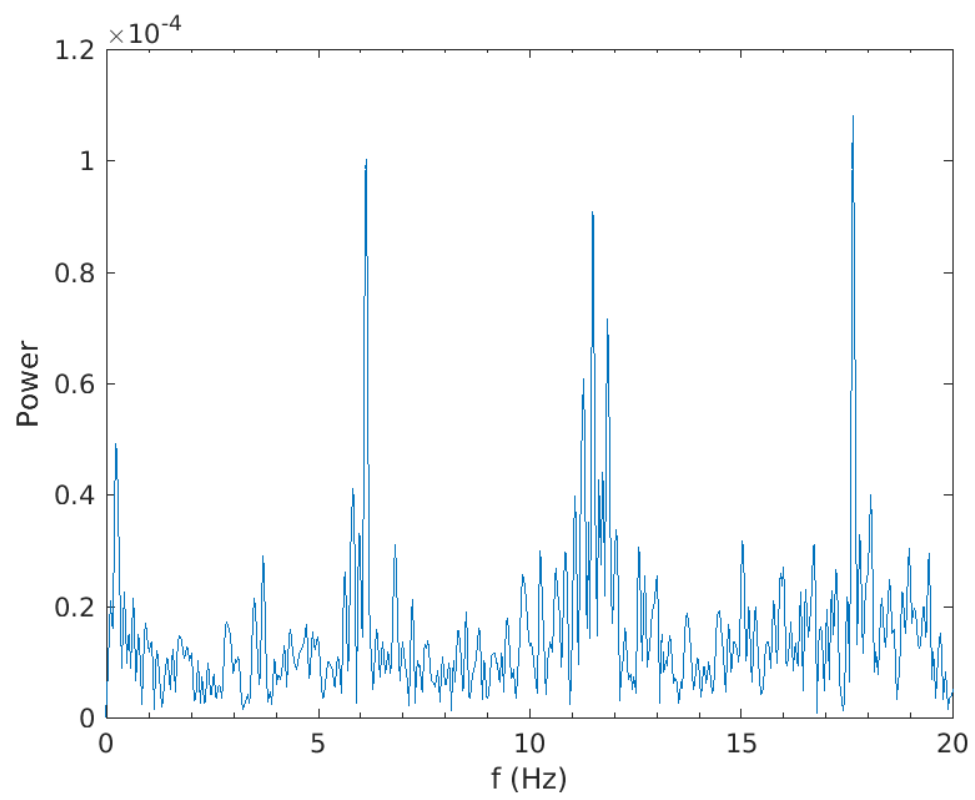


Figure 5.31: The calculated FFT of the raw acoustic emission signal from healthy gearbox calculated using Hanning window.

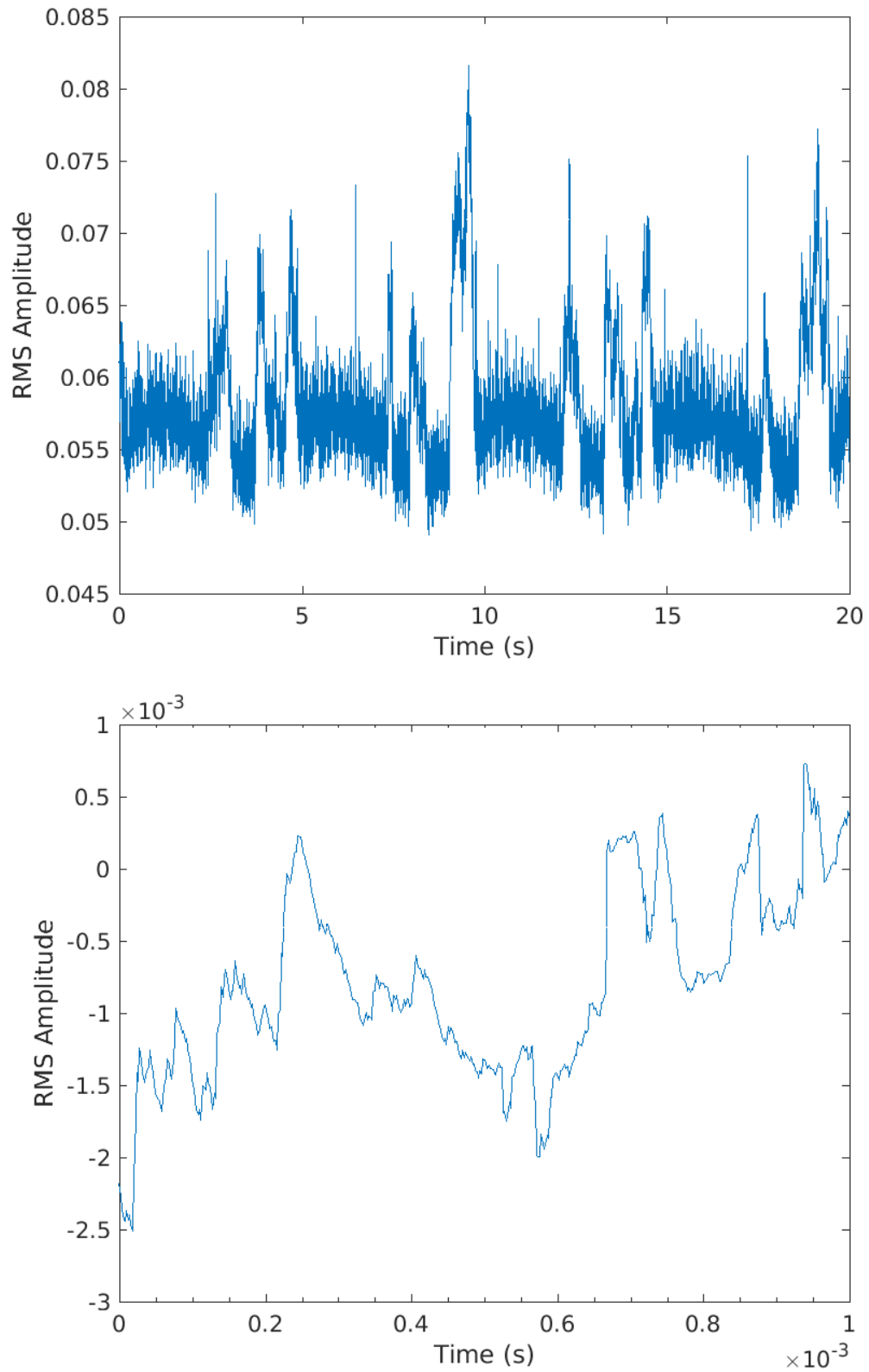


Figure 5.32: The demodulated signal using RMS technique with a window size of 1ms (FS/1000) calculated from acoustic emission signal of the gearbox with imbalanced condition showing the entire signal on top and zoomed in on bottom (mean removed).

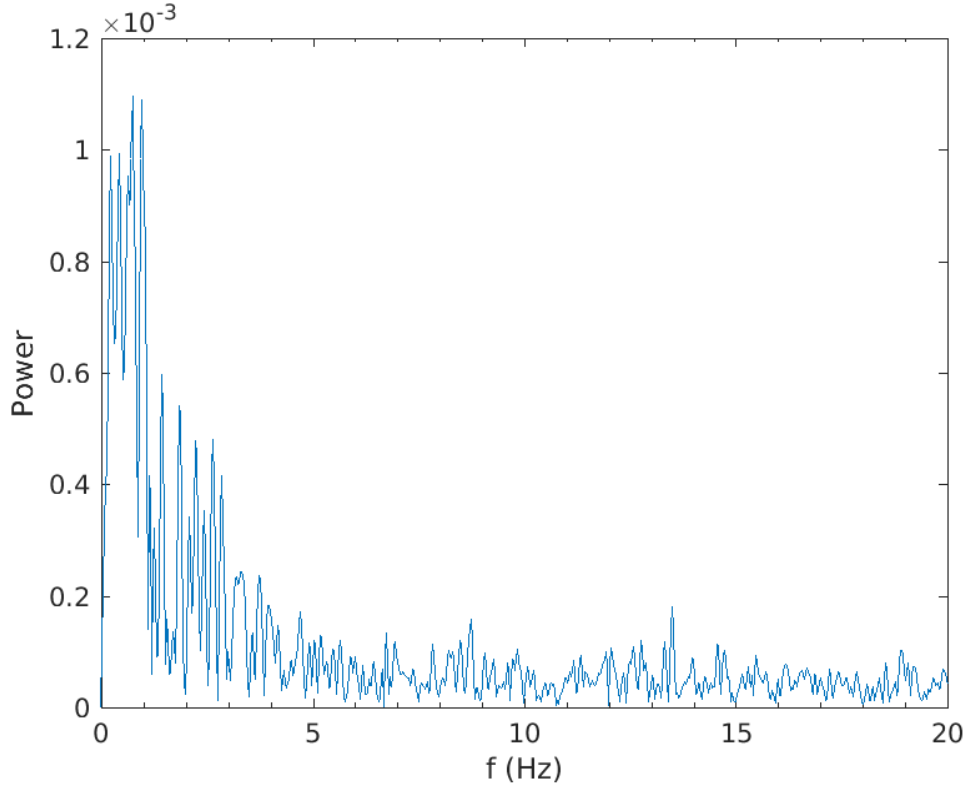


Figure 5.33: The calculated FFT of the demodulated signal from healthy gearbox calculated using Hanning window.

techniques, such as continuous wavelet transform and the results were compared. As the damage was induced at the output stage (3rd stage) it is expected to give rise to peaks in the output gear mesh range and more importantly in the GAPF frequency (listed in Table 5.4).

As it can be seen in figure 5.36, the signal became much noisier than impact test with high amplitude spikes distanced around 5 seconds (0.2Hz) that is corresponding to the output shaft.

The short time Fourier transform analysis applied to the signal shows similar results as the time signal evaluation. However, due to the high level of background noise, not much extra information is achievable by performing STFT. Figure 5.37 shows the short time Fourier transform applied on both raw signal and RMS signal.

The spectrum of the raw signal is also clearly showing the damage as shown in figure 5.38 However, the demodulated spectrum (spectrum of RMS signal) is not showing

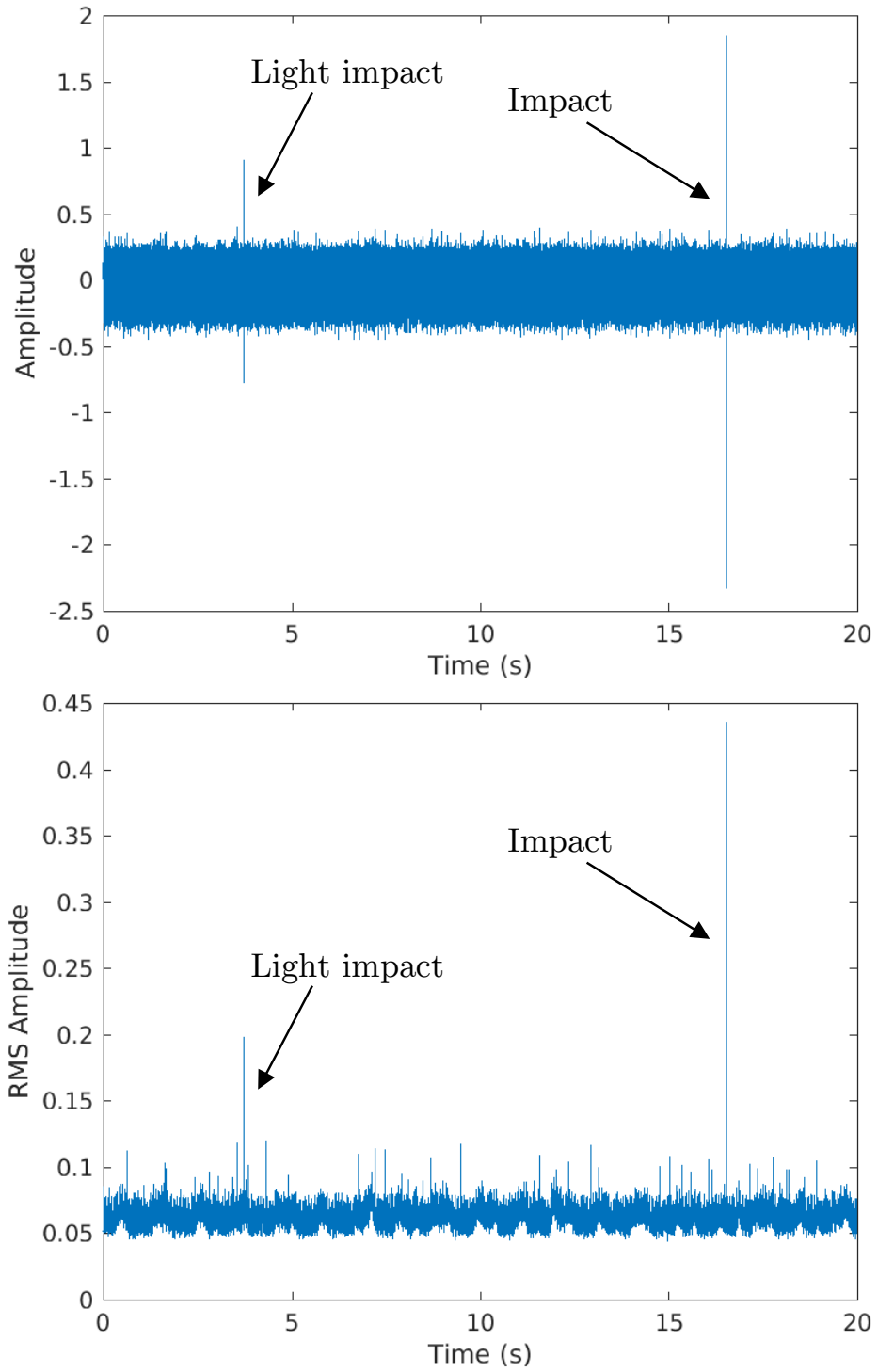


Figure 5.34: The recorded time signal and calculated RMS signal (1ms window) from mock turbine using acoustic emission sensor.

any distinguishable feature.

Unlike frequency spectrum of the signal, the wavelet transform results were consid-

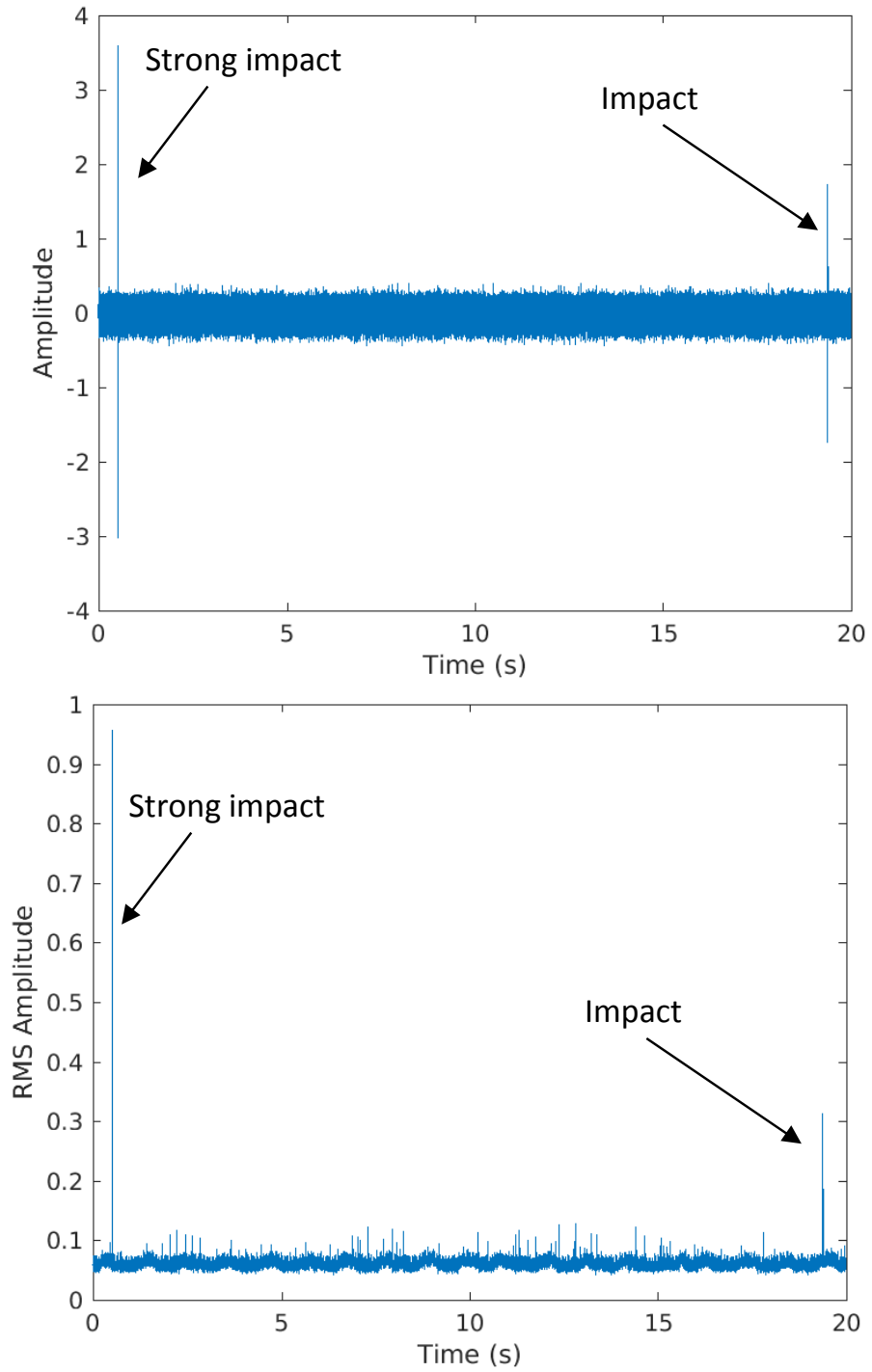


Figure 5.35: The recorded time signal and calculated RMS signal (1ms window) from mock turbine using acoustic emission sensor

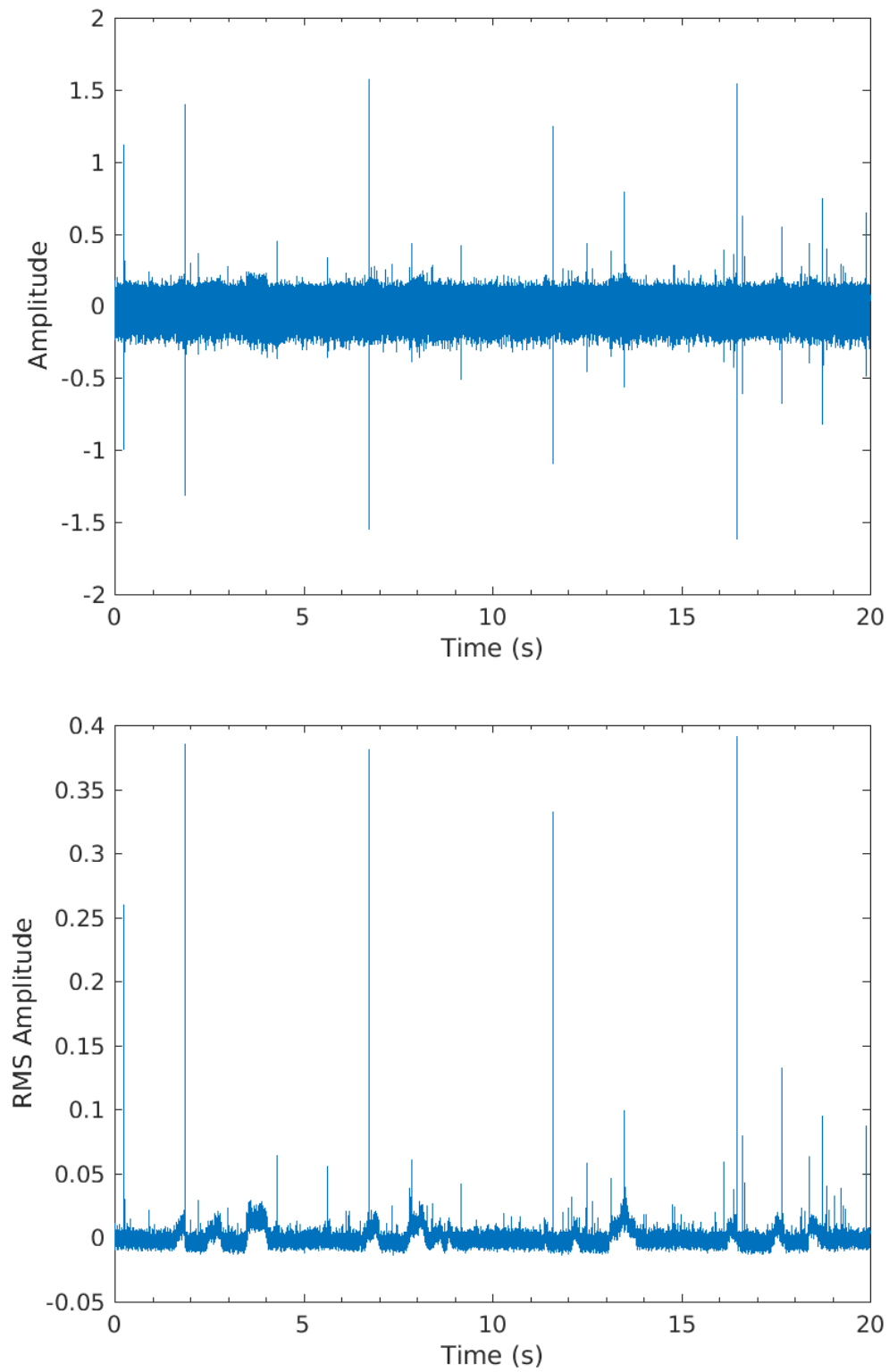


Figure 5.36: The time signal and RMS value of the mock tidal turbine with induced defect at the output stage.

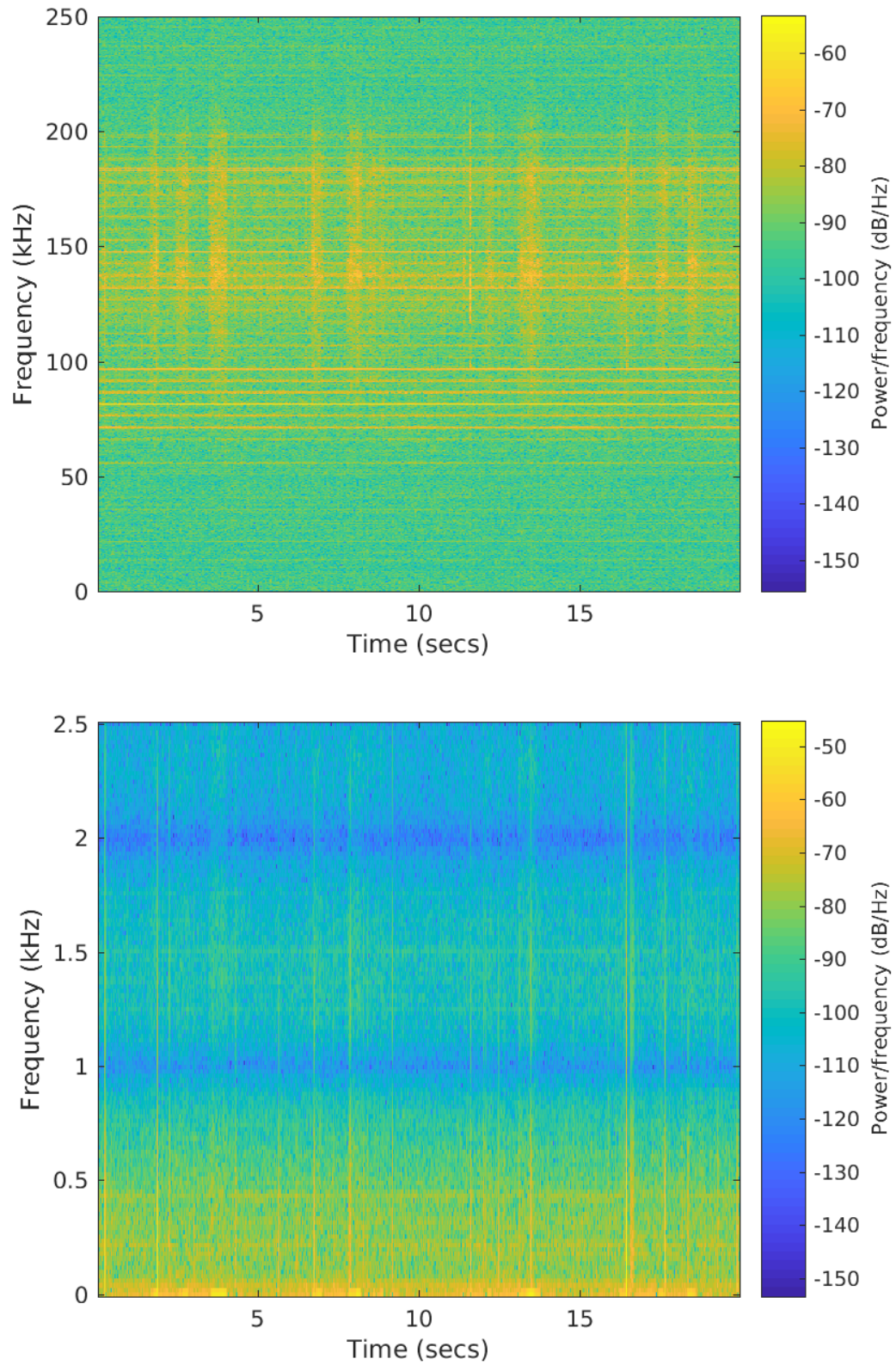


Figure 5.37: The short time Fourier transform of the signal recorded from mock tidal turbine with induced defect at the output stage; top: STFT on raw signal, bottom: STFT on RMS signal.

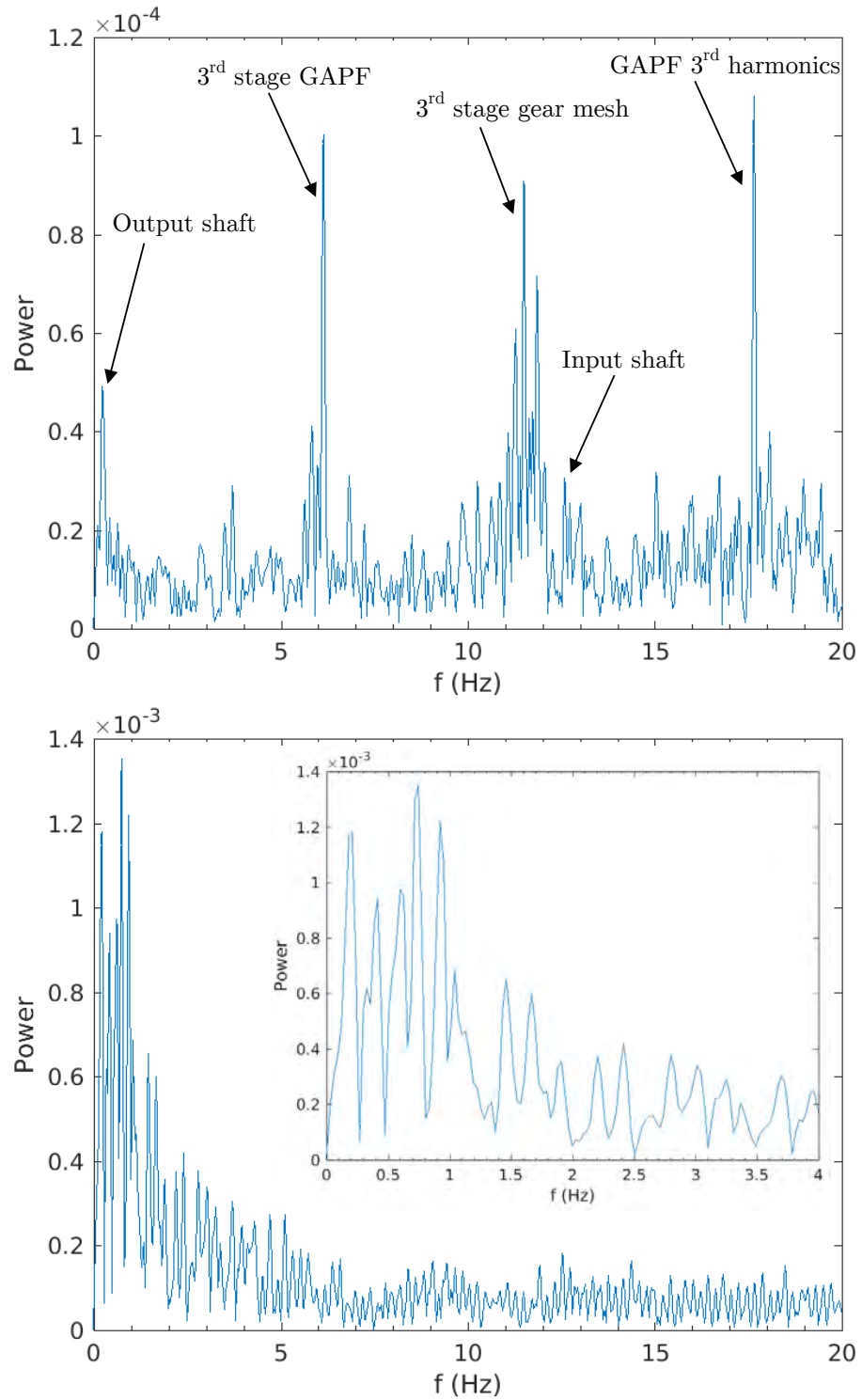


Figure 5.38: Hanning windowed FFT spectrum of the signal recorded from mock tidal turbine with induced defect at the output stage; top: STFT on raw signal, bottom: STFT on RMS signal.

erably improved by enveloping technique and the noise was significantly reduced. The results are shown in figure 5.39.

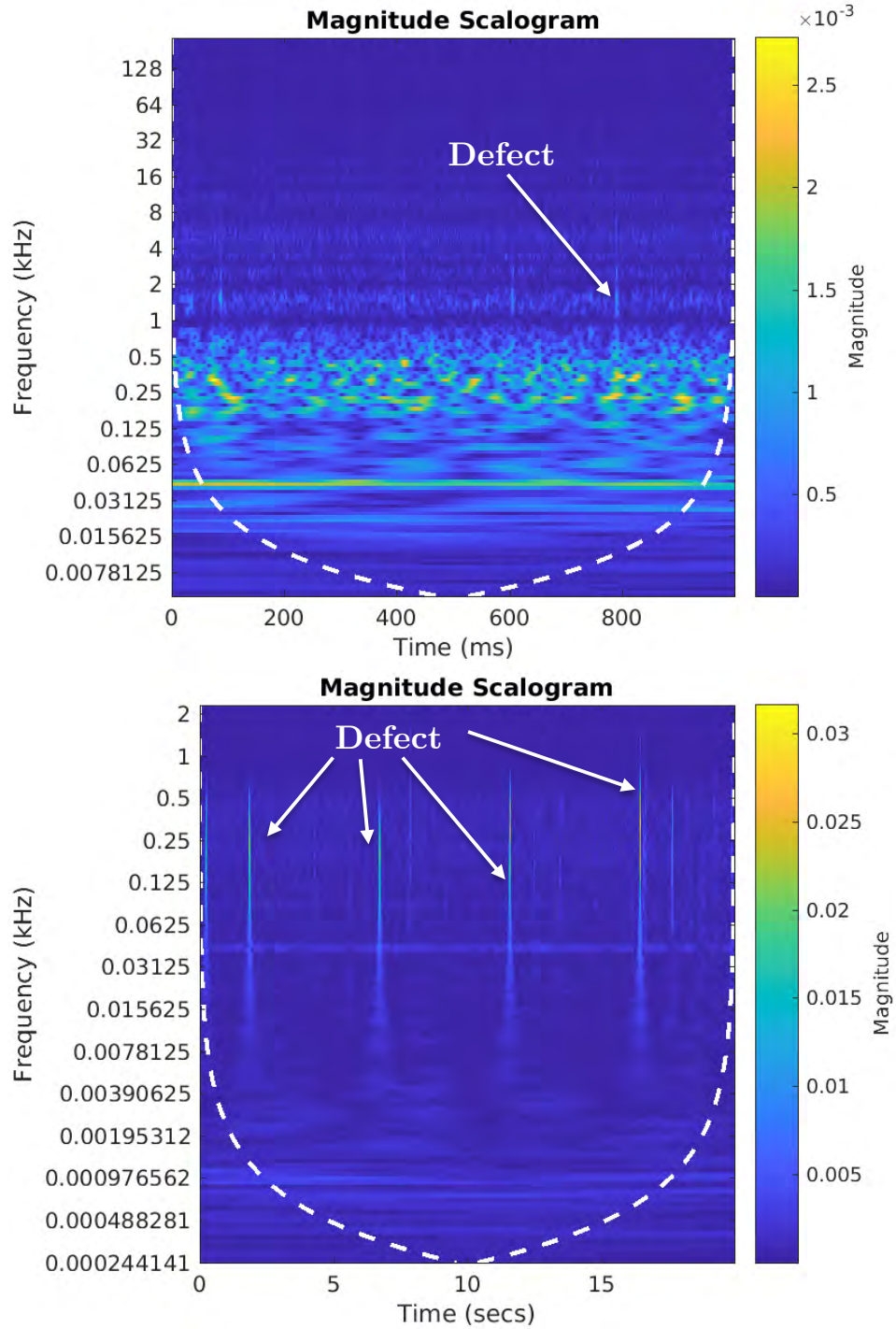


Figure 5.39: Wavelet transform of the signal recorded from mock tidal turbine with induced defect at the output stage; top: Wavelet Transform on raw signal, bottom: Wavelet Transform on RMS signal.

5.5.4 Vibration analysis of gearbox

The first condition tested was the effect of impact on the rotor blades. As it was mentioned earlier, impact can be caused by objects moving with the water flow or marine life hitting on the rotor of the turbine. It is important to recognise and monitor these types of damage on the turbine as such impacts can cause damage to the bearings apart from the blades. Figure 5.40 shows the raw signal recorded during the impact.

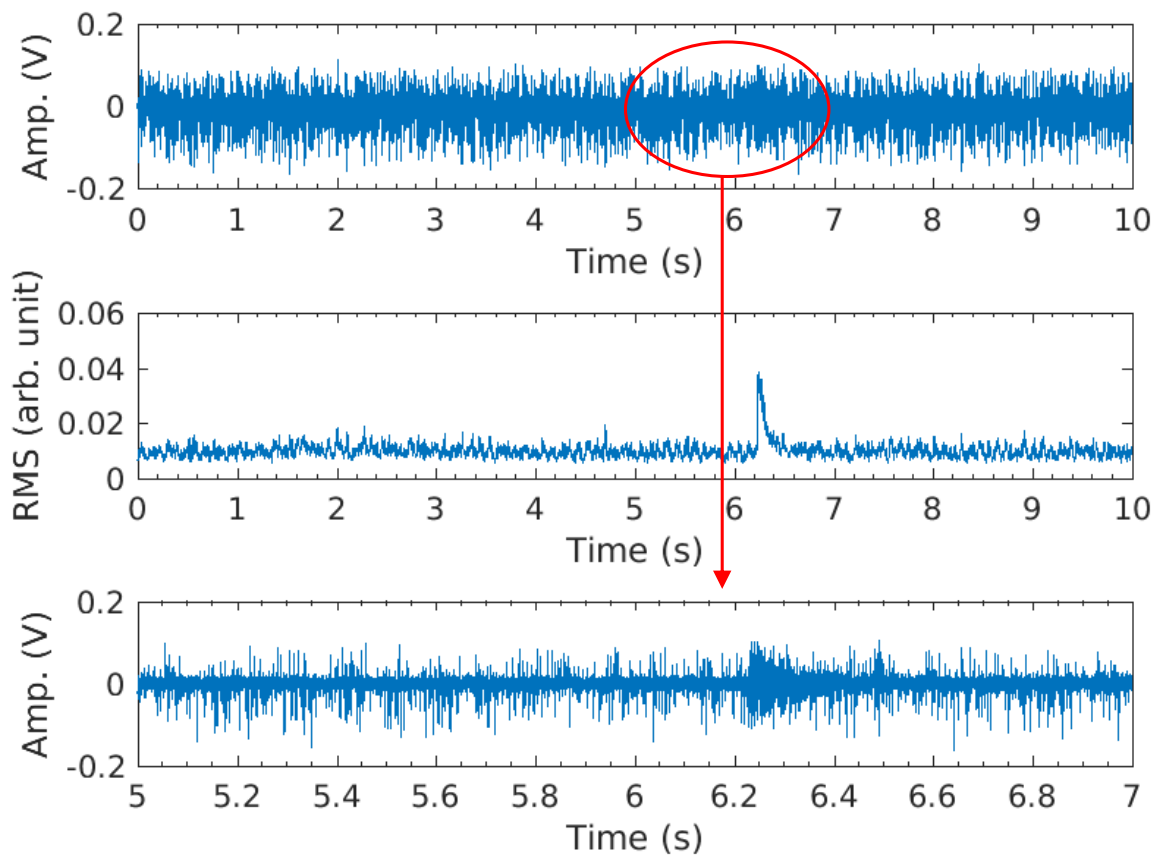


Figure 5.40: Time signal showing the effect of impact on the gearbox (top) and the moving RMS signal calculated from the signal (middle). The bottom signal is a small section of the top signal magnified for better visualisation.

The change in the amplitude of the raw signal will not be visible unless the impact is very strong and severe. However, these types of incidents can be extracted with the moving RMS (enveloping) as it is shown in the Figure 5.40 (middle). Any small impacts on the gearbox cause a sharp peak in the moving RMS. Here a window length equal to a

100th of sampling frequency ($F_s/100$) has been chosen to calculate the RMS value.

However, due to the nature of the impact signal, a very wide spectrum will result. The spectrum of the signal will not provide much information about the impact itself as it is shown in figure 5.41 (bottom). Nevertheless, this can be modified by shortening the FFT window size and analysing the spectrum over a short time window as in figure 5.41 (top).

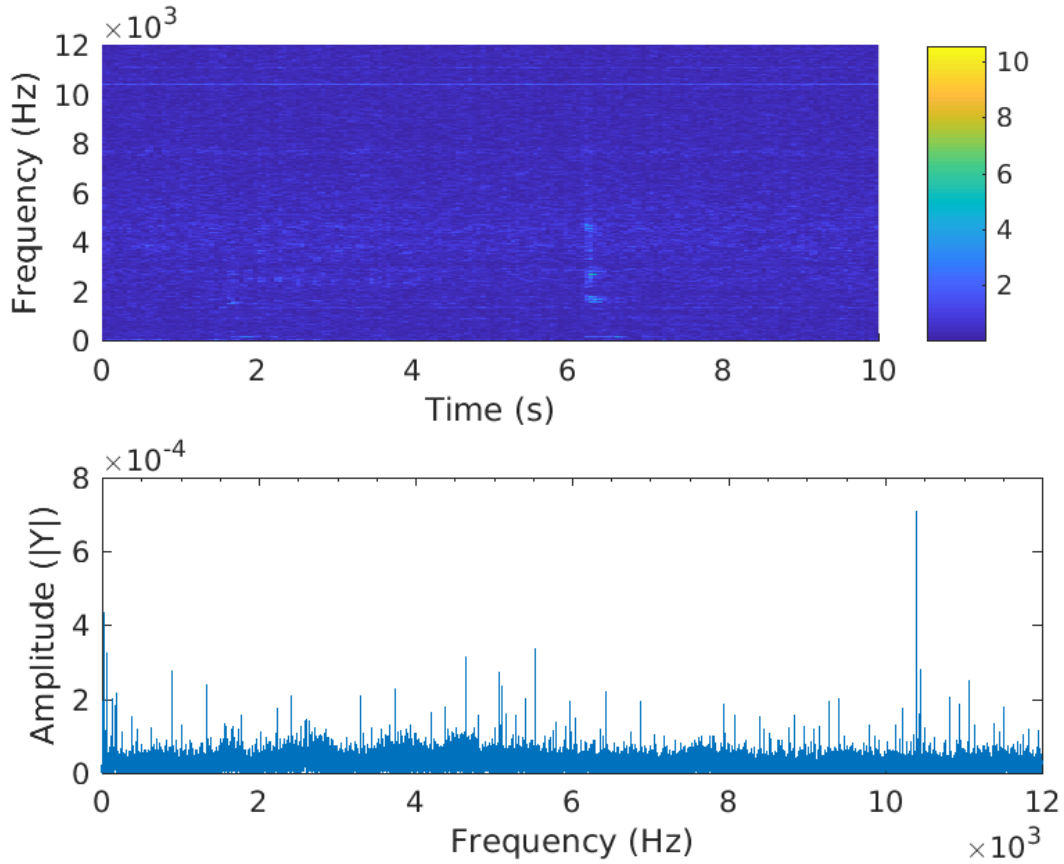


Figure 5.41: The short window FFT spectrum analysis of the signal recorded from gearbox during occurrence of impacts (top) and the full spectrum of the same signal (bottom)

The imbalanced rotor can lead to the development of a fault in the gearbox. The imbalanced rotor will produce a periodic vibration in the signal. It was found that the fault can be detected using moving RMS. This defect unlike impact causes sharp peaks in moving RMS, has relatively wider peaks distributed evenly over the signal with proportionality to the speed of the unbalanced rotor. Figure 5.42 shows the raw time signal recorded from an unbalanced rotor. Although the variation in the signal is noticeable, it

cannot be used as a certain measure while the moving RMS analysis shown in figure 5.43 clearly highlights the fault.

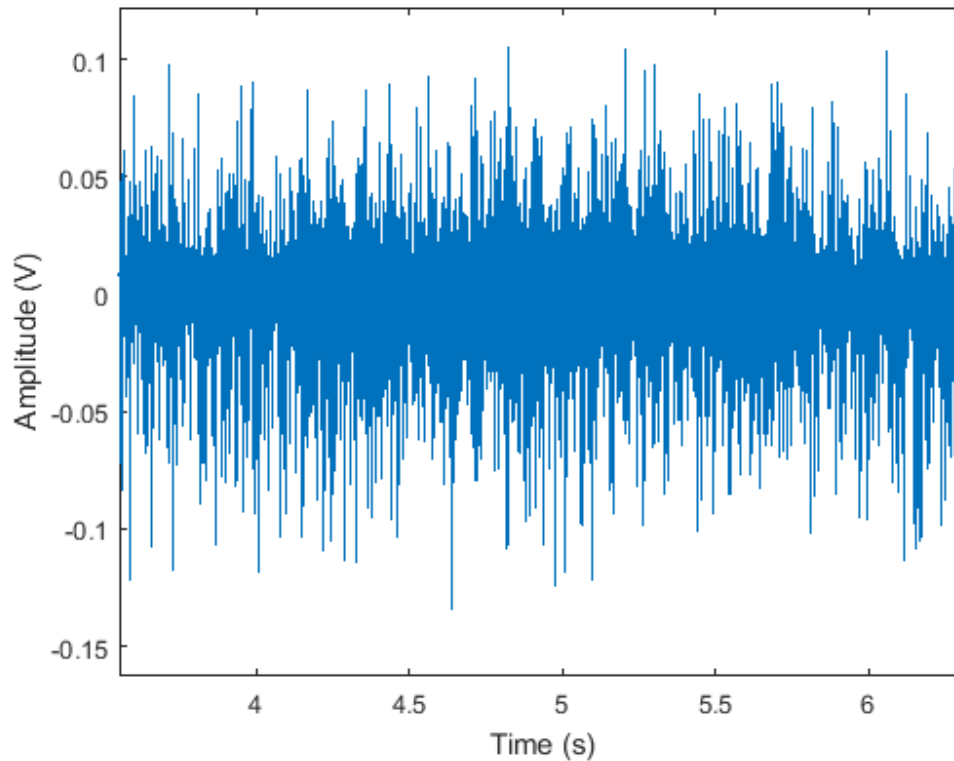


Figure 5.42: Raw time signal recorded using vibration sensor from the gearbox with imbalanced rotor

Figure 5.44 shows another unbalanced rotor identified using moving RMS. The evenly spread peaks over the time make the fault distinguishable from other type of faults.

Another technique to identify imbalance of the rotor is through HFRT analysis. This technique better than the moving RMS technique as the observed peaks in the spectrum can be related to a particular gear or shaft. Figure 5.45 shows the HFRT analysis of an unbalanced rotor and the relevant peaks from Table 5.4 that are available in the spectrum are marked.

The first two markers represent the shaft 2 and shaft 3 natural frequencies that suggest the imbalanced rotor is between shaft 2 and 3. This will consequently result in an increase of the vibration at gear mesh frequencies of 35.5 and 5.5 Hz. The 5.5 Hz is the GAPF frequency that is a fraction of gear mesh due to the number of gear teeth not being a

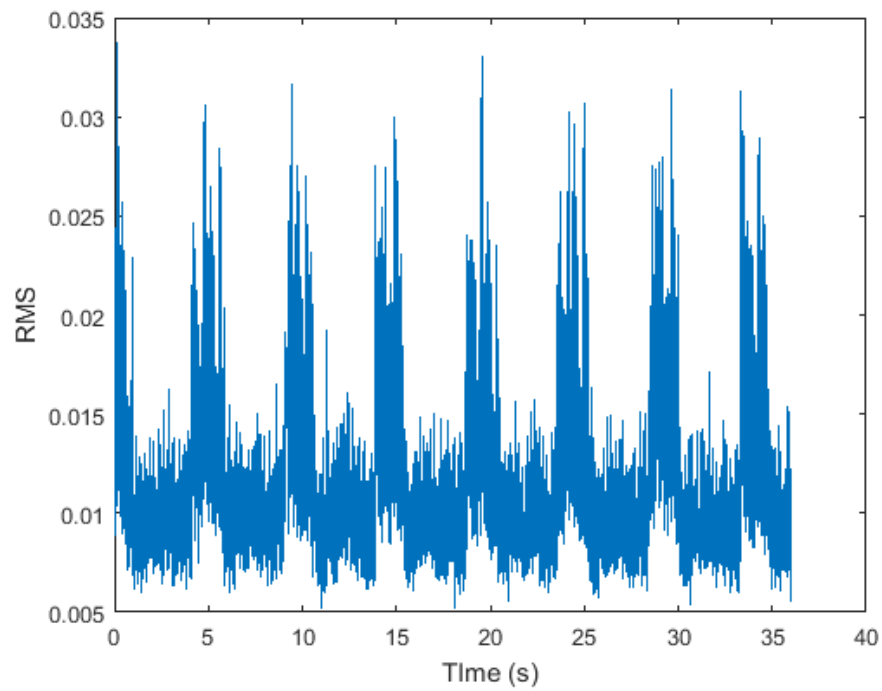


Figure 5.43: Moving RMS analysis on the vibration signal recorded from the gearbox with imbalanced rotor (First record).

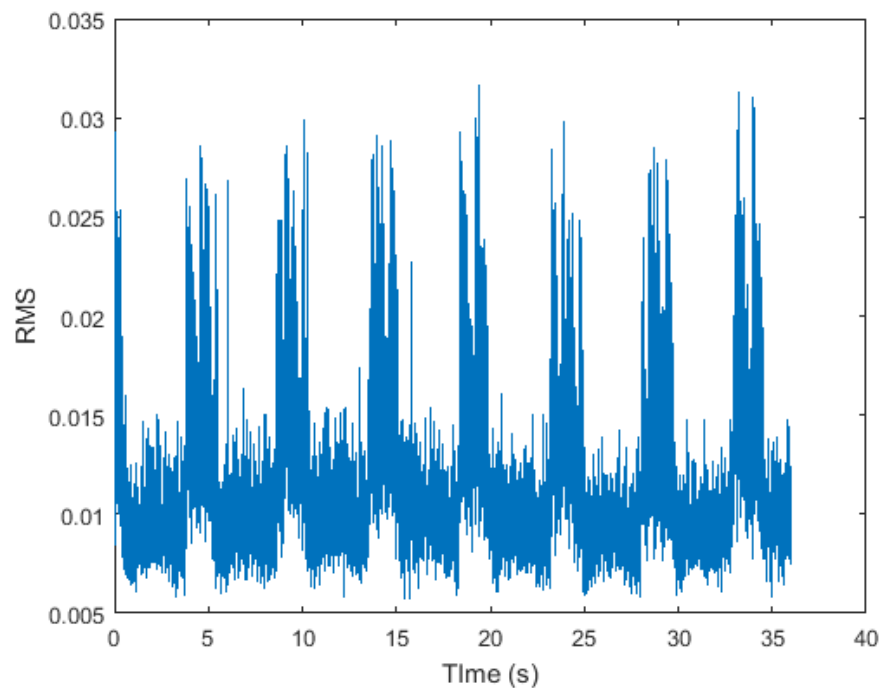


Figure 5.44: Moving RMS analysis on the vibration signal recorded from a gearbox with imbalanced rotor (second record).

prime number. The high amplitude peak located at 21.35 Hz is the sixth harmonic of interim shaft A. The third harmonic of interim shaft A at 10.65 Hz, is also noticeable. This behaviour is most likely due to tooth wear which will increase the amplitude of the harmonics.

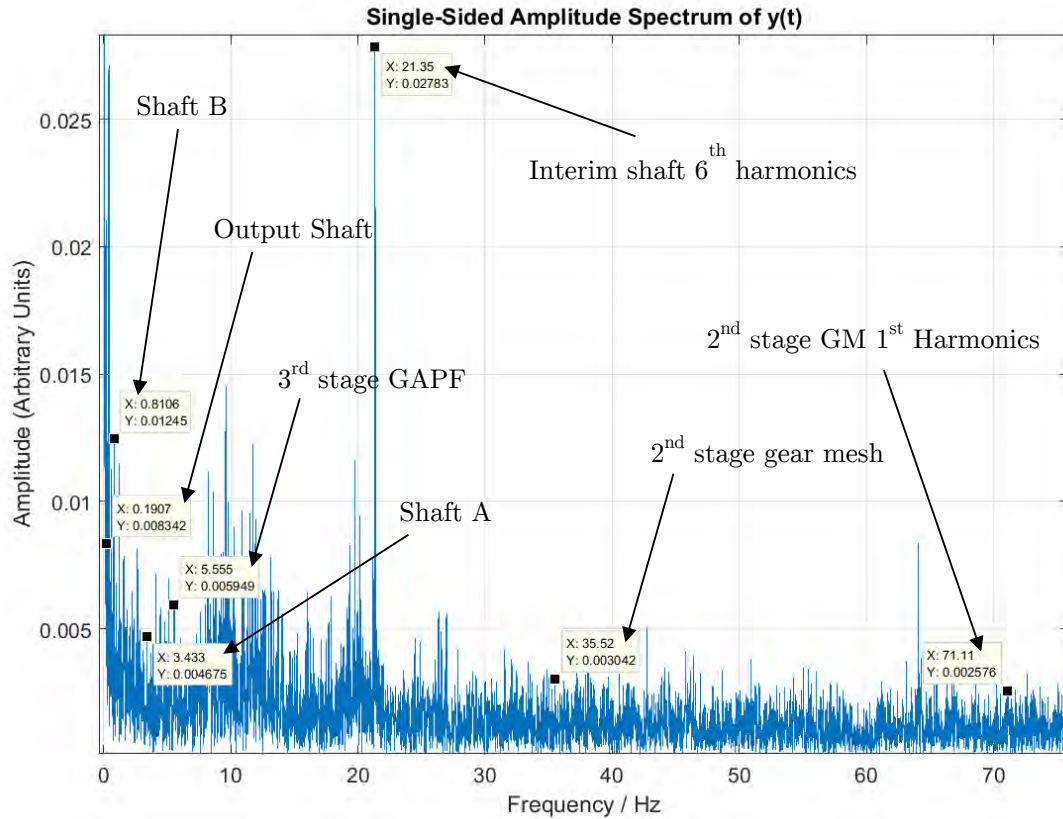


Figure 5.45: HFRT analysis of the vibration signal recorded from the gearbox with imbalanced rotor showing 2nd and 3rd stage frequencies corresponding to imbalanced rotor.

Finally, induced wear on the gear teeth as it is shown in figure figure 5.4 was investigated using vibration analysis. Similar to the acoustic emission signal, the damaged teeth cause sharp spikes on the vibration signal as it can be seen in figure 5.46. However, the spectrum of the vibration signal (Figure 5.47) is noisier than acoustic signal and the characteristic frequencies are less obvious.

Unlike acoustic emission, the short time Fourier transform of the vibration signal reveals the fault with better contrast and it is easily identifiable. This is shown in Figure 5.48.

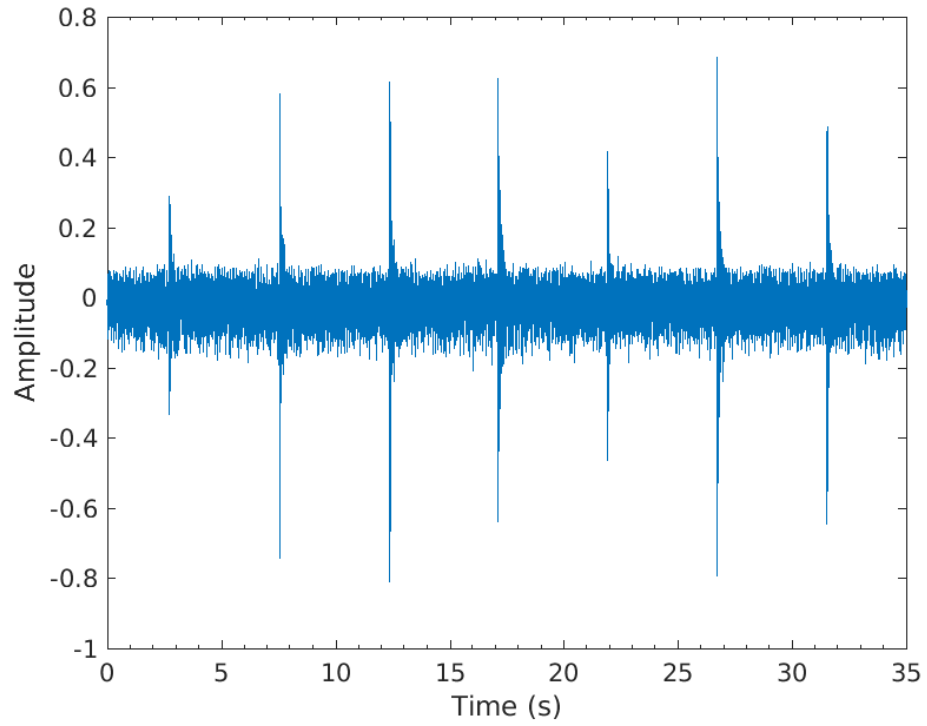


Figure 5.46: The time signal of the mock tidal turbine with induced defect at the output stage recorded using vibration sensor.

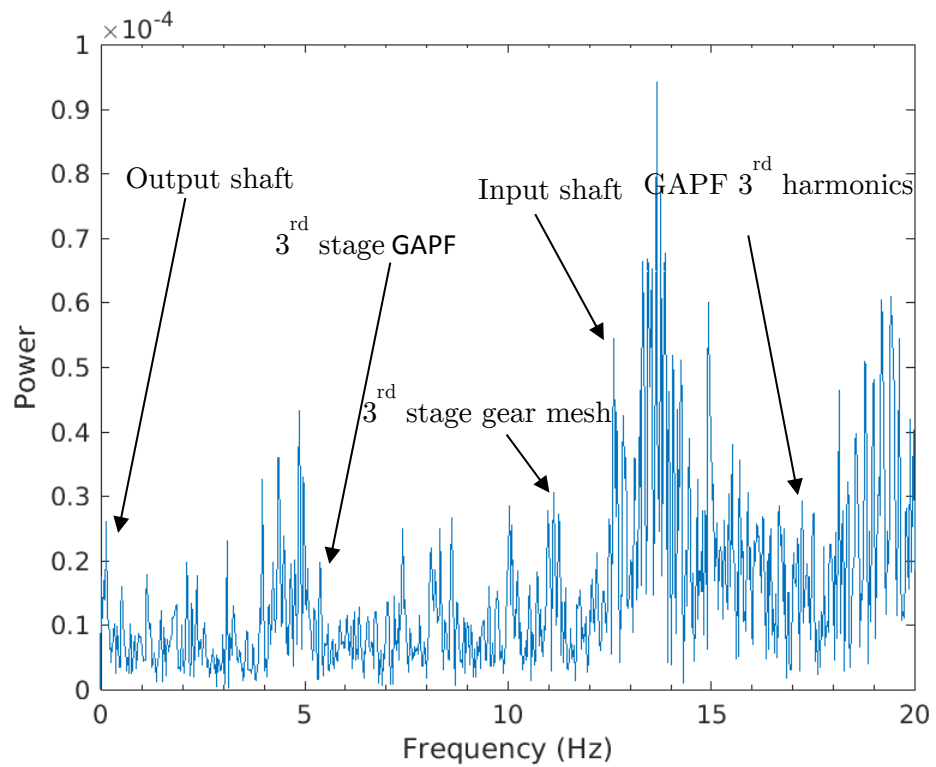


Figure 5.47: The calculated FFT of the vibration signal of the mock tidal turbine with induced defect at the output stage using Hanning window.

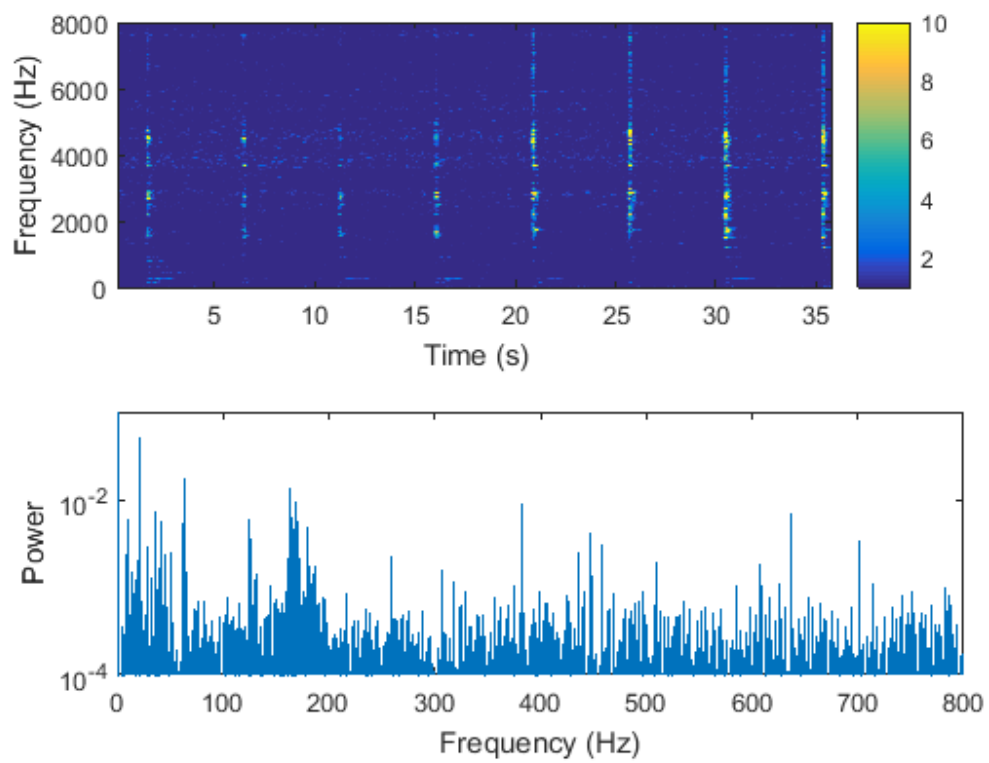


Figure 5.48: The calculated short time FFT (top) and FFT (bottom) of the vibration signal of the mock tidal turbine with induced defect at the output stage using Hanning window.

The wavelet transform of the signal is also revealing the defect as shown in figure 5.49. Both short time Fourier transform and wavelet transform give similar levels of contrast and highlight the presence of the defect clearly.

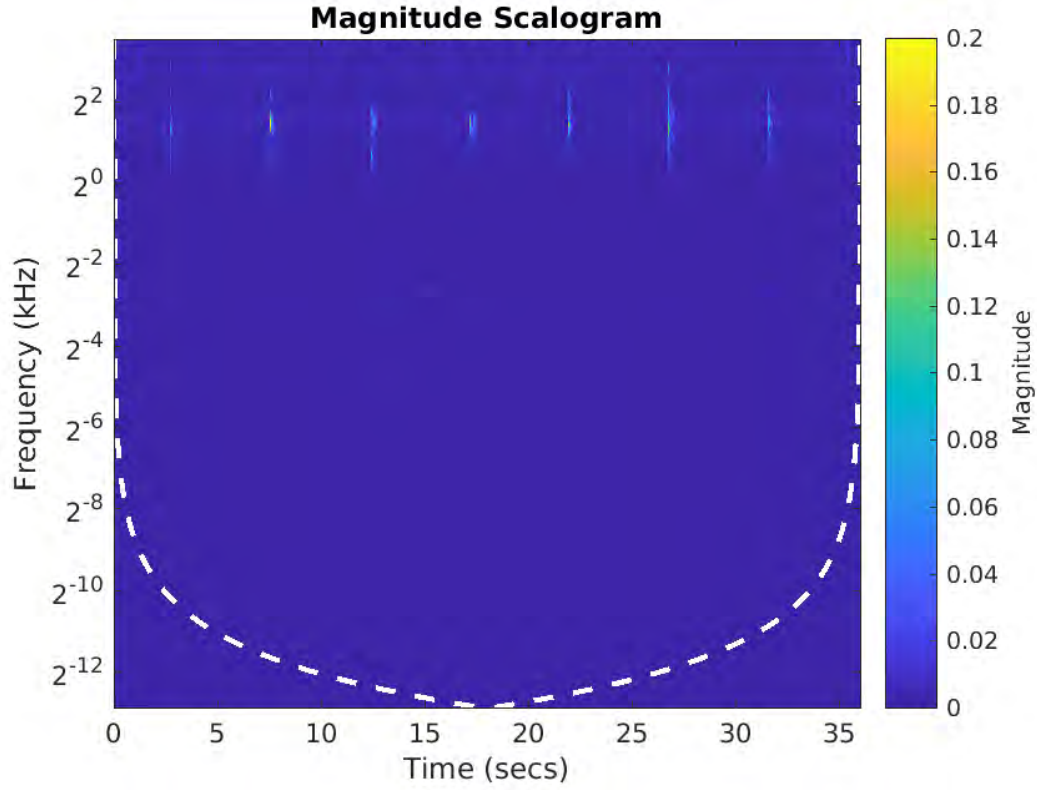


Figure 5.49: Wavelet transform of the signal recorded from mock tidal turbine with induced defect at the output stage.

Comparing the acoustic emission and vibration signals ability to identify the defect and gives distinct results, it can be said that they complement each other and if used together, they will be able to clearly identify the fault in the system in a more accurate and quantifiable way.

5.6 Summary

In this chapter the effectiveness of different signal processing techniques performed on both vibration and acoustic signals to indicate degradation and fault in the system were investigated. Induced faults on bearings and gears inside a gearbox in isolated and con-

trolled environment were identified using different techniques. However, in reality, the prior knowledge about the fault is not available and the signal is significantly contaminated by noise and vibration generated in different parts of the turbine.

The next chapter will consider the signals recorded from industrial wind turbines to evaluate the suitability and performance of these signal processing techniques to identify faults in large scale industrial wind turbines.

“Nothing in life to be feared, it is only to be understood. Now is the time to understand more, so that we may fear less.”

— *Marie Curie*

Chapter 6

Industrial wind turbine field trials

6.1 Introduction

In the previous chapter it was shown that the developing faults in the gearbox can be detected in early stages using various condition monitoring techniques. However, unlike the controlled environment and laboratory tests based on the bearing test rig and mock-up tidal turbine, actual wind turbines have a much denser frequency content since a considerable amount of noise is picked up by the sensors. This makes data analysis much harder and fault detection becomes even more challenging.

In this chapter, the data recorded using vibration and acoustic emission sensors from three different types of real wind turbines (1.5 MW, 850 kW and 600 kW models) have been studied and analysed. Due to confidentiality and copyright, the wind turbine names and models as well as some of the technical details or bearing models have not been disclosed. The used three wind turbines have thus been dubbed as M1, M2 and M3 respectively with decreasing nominal power output.

6.2 Wind turbine M1

6.2.1 Specifications

The M1 wind turbine is a 1.5MW geared wind turbine as shown in figure 6.1. It is part of a wind farm with 33 wind turbines (49.5MW total nameplate capacity). The M1 wind turbine has a rotor diameter of 82 metres and its nominal rotational speed of the rotor is 16.7 RPM. The rotor is connected to a multi-stage planetary gearbox with 1:65.98 ratio. The high-speed shaft at the generator has a nominal speed of 1100 rpm.

The schematic diagram of the 3-stage gear train used in wind turbine M1 is presented in figure 6.2 along with number of gear teeth, bearing positions and stage ratios. The bearing models corresponding to the numbered positions are listed in Table 6.1 with corresponding defect frequencies calculated using Table 3.5 for a speed of 60 RPM (1 order) at the output or high speed shaft of the gearbox (i.e. generator). The actual fault frequencies is calculated using this table by multiplying these frequencies by the generator speed (in Hz).

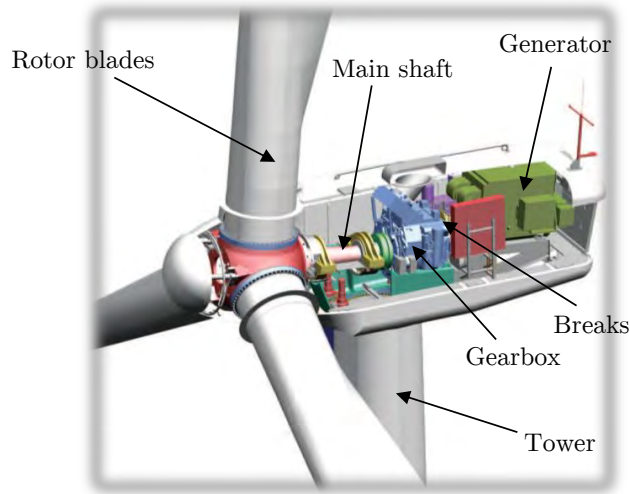


Figure 6.1: The instrumented wind turbine M1.

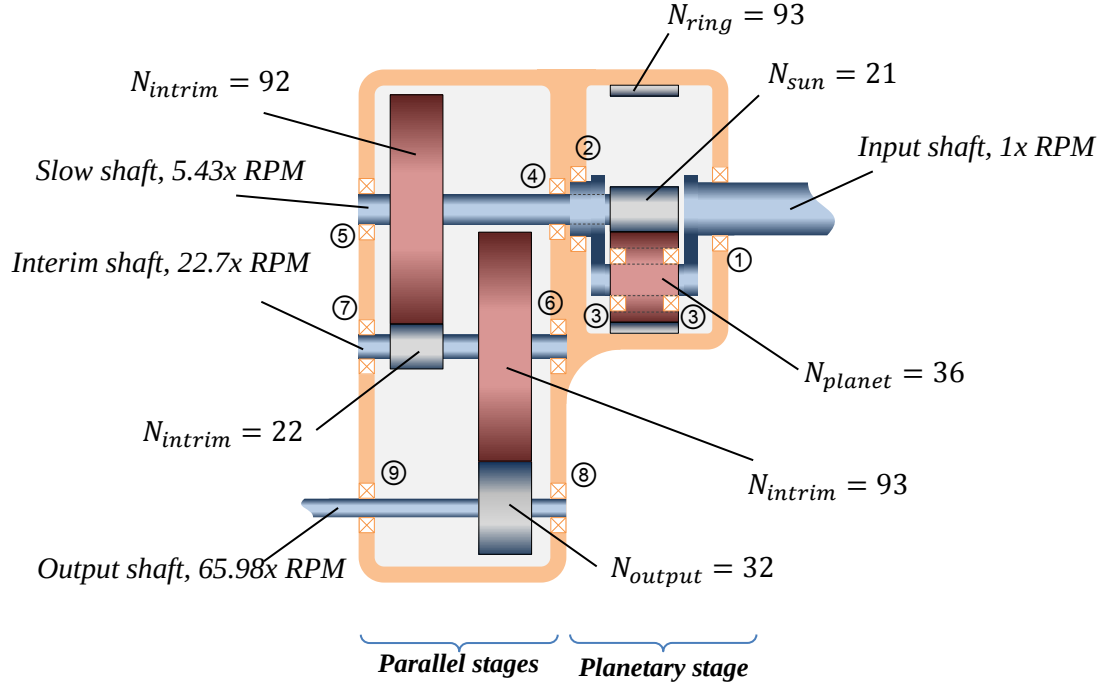


Figure 6.2: The gearbox used in wind turbine M1.

Table 6.1: The bearing frequencies calculated in Hertz for the wind turbine M1 with 60 rpm (1 order) speed at generator

Position No.	Model	FTF	BSF	BPFO	BPFI
1	NCF 18/560V	0.007	0.147	0.439	0.486
2	NCF 2980V	0.007	0.094	0.272	0.319
3 (X6)	RN2338	0.022	0.130	0.282	0.424
4	NCF 2980V	0.038	0.508	1.476	1.734
5	23984	0.039	0.624	0.154	0.175
6	NU232	0.148	1.196	2.808	3.730
7	NU2336	0.138	0.835	1.794	2.679
7	QJ334	0.143	0.796	1.853	2.621
8	NU2326	0.403	2.491	5.647	8.353
9	NU328	0.405	2.548	5.676	8.324
9	QJ328	0.412	2.237	4.938	7.062
Sun shaft	6026	0.007	0.060	0.100	0.128

6.2.2 Instrumentation

The instrumentation of the wind turbine drive-train was carried out by one of the industrial project partners (Indra). Four types of accelerometers have been used to record the frequencies of interest along the drive-train path. The choice of sensor selection was based on the frequency range of interest at each stage of the gearbox. For example, the low speed shaft and planetary stage gears produce significantly lower range of frequencies compared with the high-speed shaft. The summary of the used sensors is tabulated in Table 6.2.

The sensors are fixed in place directly on the body of the wind turbine drive-train using an epoxy-based adhesive as shown in Figure 6.4 and Figure 6.5. The tachometer was fixed using bi-component putty as shown in Figure 6.6.

The accelerometers employed are classified into three main groups. First, the low-speed sensors to monitor the low frequencies near the low speed shaft (drive end), second, the high-speed sensors, installed on the intermediate and high-speed shafts and the generator. Finally, the speedometer located on the high speed shaft before the generator. The location of each sensor on the drive-train is specified schematically in figure 6.3 and listed in details in Table 6.3.

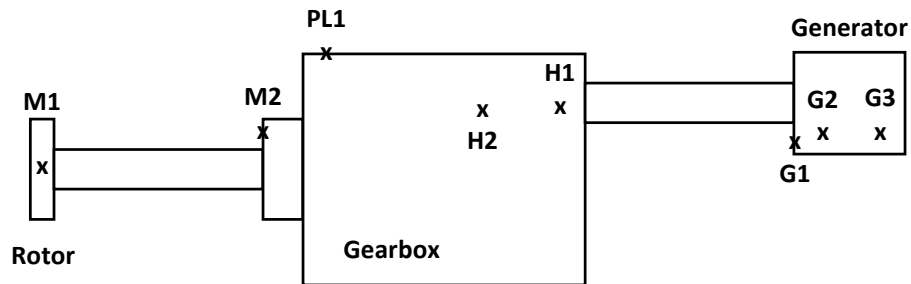


Figure 6.3: Instrumentation of the drive train of M1 wind turbine by INDRA

The installed sensors were connected to the data acquisition unit (SIMAP) which has been developed by Indra and it is shown in figure 6.7.

The low frequency sensors (L1-L4) are initially recorded for 102.4 seconds (716,800

Table 6.2: Summary of the used sensors, their sensitivity, range and models.

Model	Sensitivity	Range	Connection	Picture
KS80D	100 mV/g	0.13 to 22000 Hz	Binder 713	
608A11	100 mV/g	0.5 to 10000 Hz	Moulded integral cable	
4519-001	100 mV/g	0.5 to 20000 Hz	M3	
4513-001	100 mV/g	0.5 to 10000 Hz	10-32 UNF	
ROS-5P	—	1 to 250000 rpm	M8S Straight P	

Table 6.3: Summary of installed sensors along the wind turbine drive-train including their name, model and location

Sensor	Signal	Channel	Model	Direction	Location
L1	RPEH	0	KS80D	Horizontal	Main bearing input
L2	RPSV	1	KS80D	Vertical	Main bearing output
L3	MEV	2	KS80D	Vertical	Planetary gears (Low speed)
H1	MIV	8	608A11	Vertical	High speed bearing (Intermediate zone)
H2	MSV	9	608A11	Vertical	High speed bearing (gearbox output)
L4	MSH	3	KS80D	Horizontal	Low speed bearing (gearbox output)
H3	GAR	10	4519-001	Oblique	Generator input
H4	GCR	11	4513-001	Oblique	Generator output
T1	TACO	TACO	ROS-5P	—	High speed shaft

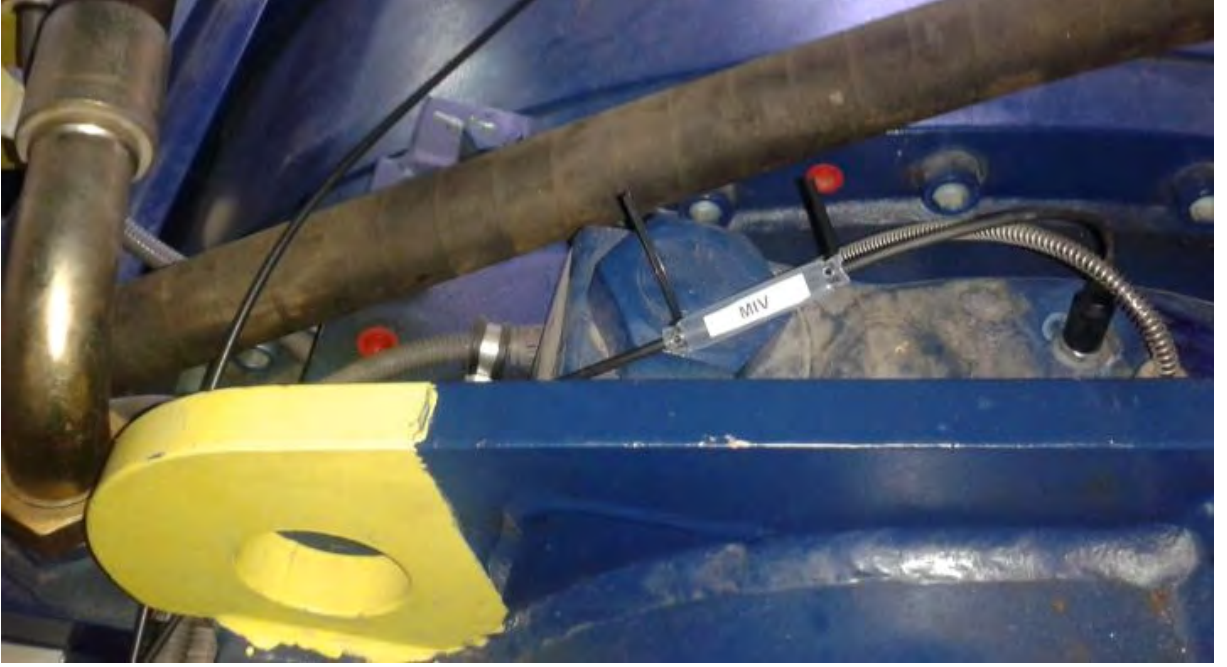


Figure 6.4: The H1 (MIV) sensor on top of the high-speed bearing of the gearbox (Photograph is courtesy of Indra).

samples) with a sampling rate of 7 kHz while the high frequency sensors (H1-H4) are recorded for 2.72 seconds (51,195 samples) with sampling rate of 22.5 kHz to reduce the data size. Next, the initial recordings are further filtered using a digital filter into several sub-frequency bands, for easier analysis. These sub-bands are listed in Table 6.4. This will produce a total of 24 data files for each monitoring frame.

However, the recording approach was altered later on in the project and the data were collected without applying the digital filter with a sampling rate of about 24 kHz and duration of 10.9 seconds (262,144 samples) for both low frequency and high frequency sensors.

6.2.3 Data analysis

The original recorded data files are in binary format and have been converted to a MATLAB compatible format. The converted data files were then analysed for presence of any defect frequency, calculated using the equations listed in Table 3-3 and Table 3-5 at each instance based on the relevant wind turbine blade speed. Table 6-5 presents these



Figure 6.5: The L3 (MEV) sensor located on top of the planetary gearbox (Photograph is courtesy of Indra).

Table 6.4: Applied digital filter on the recorded data from M1 drive-train acquired by Indra

Sensor number	Filter number	Lower frequency (Hz)	Top frequency (Hz)	Decimation factor	Truncation (number of samples)	Final sample frequency (Hz)
L1-L4	F1	0	2	1400	512	5
L1-L4	F2	1.1	7	400	512	17.5
L1-L4	F3	7	280	10	8192	70
L1-L4	F4	280	2800	1	4096	7000
H1-H4	F5	7.35	180	50	1024	450
H1-H4	F6	180	9000	1	8192	22500



Figure 6.6: The tachometer installed on the high-speed shaft going to the generator (Photograph is courtesy of Indra).

Figure 6.7: Indra condition monitoring data acquisition module (Photograph is courtesy of Indra).

frequencies calculated for the nominal speed of 1100 RPM at the high-speed shaft. The presence and variation of these frequencies has been investigated over several months to obtain characteristic trends that may signify damage in one of the gearbox components.

Table 6.5: M1 Gearbox frequencies based on 1100 rpm nominal output

Parameter	RPM	Hz
High speed shaft (output)	1100.00	18.33
Speed		
Interim shaft 2 speed	378.49	6.31
Interim shaft 1 speed	90.51	1.51
Input shaft speed	16.67	0.72
Gear Mesh		
GM Stage 3	35200	586.67
GM Stage 2	8326.88	138.78
GM Stage 1	4651.72	77.53
Defect Frequencies		
Sun gear	221.51	3.69
Ring gear	50.02	0.83
Planetary gear	86.14	1.44

Figure 6.8 illustrates and compares the F3 band frequency (7-280 Hz) of the MEV sensor which is located on top of the planetary stage of the gearbox with a 55-days (7 weeks and 5 days) interval. Most of gear mesh frequencies exist in this frequency band. As it is shown the gear mesh frequency of the planet gears within the first stage of the gearbox (77.5 Hz) is considerably increased which can suggest a fault may be developing. Similarly, the amplitude of the second stage gear mesh has risen.

Looking at different frequency band (F1) of the same sensor (MEV) where the planetary stage defect frequencies are present, it is obvious that the defect frequency corresponding to the ring gear (0.83 Hz) has been risen by almost 10 times over the same period of time which is shown in figure 6.9. This claim can be confirmed by looking at

the signals recorded from different sensors over this time.

Observing the trend of the ring defect frequency using all four low frequency sensors over 5 months clearly shows the up-going trend in the ring defect frequency as it shown in figure 6.10. A similar rise has been observed in the sun defect frequency as shown in figure 6.11 which implies that the first stage of the gear box is likely to develop a fault requiring maintenance attention.

The trend analysis of the data is performed automatically using a customised software packaged developed during this project and discussed in Chapter 7 of the present thesis. Data averaging is performed over a period of one month, starting from 1st of month at 00:01 to 31st of month at 23:59 for each of the sensors. The standard error is calculated based on the standard deviation of the dataset divided by the square root of the number of readings. The defect frequency is calculated automatically based on the detected high-speed shaft rotational speed for each individual data file which has been extracted using frequency domain analysis.

About a year later, the operator monitoring the wind turbine observed a rising trend in the generator bearing fault frequency (BPFO) and suspected the generator bearing had been damaged. However, the signal processing performed by the author using demodulation and filtering of the signal, rejected the possibility of that particular bearing being damaged. This finding was confirmed after the bearing concerned was removed from service and microscopically evaluated revealing no defect. The details of the investigated bearing are listed in Table 6.6.

Since reports provided for this particular wind turbine had indicated the possibility of damage being present at the outer race of the generator bearing, a total of more than 15,000 data files covering a month of the wind turbine operation were analysed and averaged over a daily time frame (00:01 to 23:59) for each of the 8 sensors installed on the wind turbine by the author of the present thesis. The result is presented in Figure 6.12. The standard error is calculated as the standard deviation of the dataset divided by the square root of the number of readings.

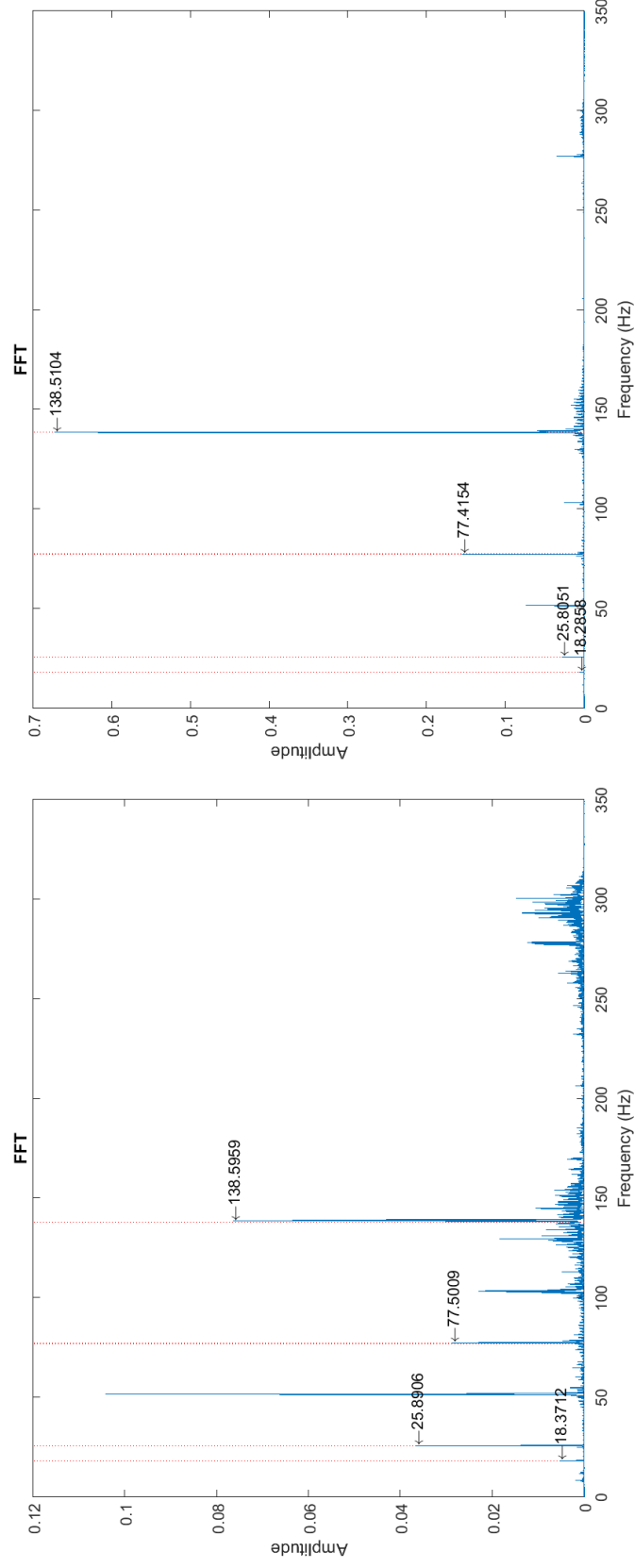


Figure 6.8: F3 band frequency (7-280 Hz) of the MEV sensor (L3), located at the planetary stage of the gearbox with a 55-days interval, showing most of characteristic frequencies considerably increased. Left: data recorded on 30/09/2014 Right: data recorded on 31/12/2014.

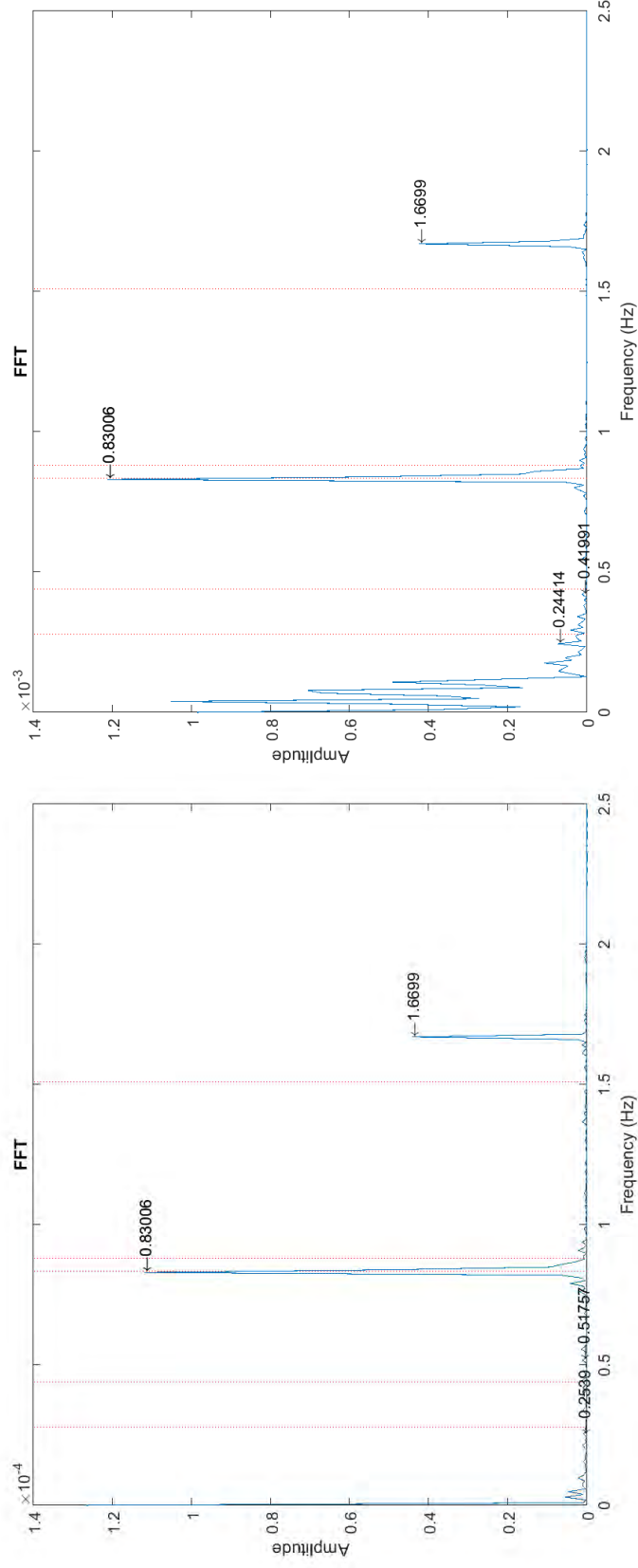


Figure 6.9: F1 band frequency (0-2 Hz) of the MEV sensor (L3), located at the planetary stage of the gearbox with a 55-days interval, showing most of characteristic frequencies considerably increased. Left: data recorded on 30/09/2014 Right: data recorded on 31/12/20.

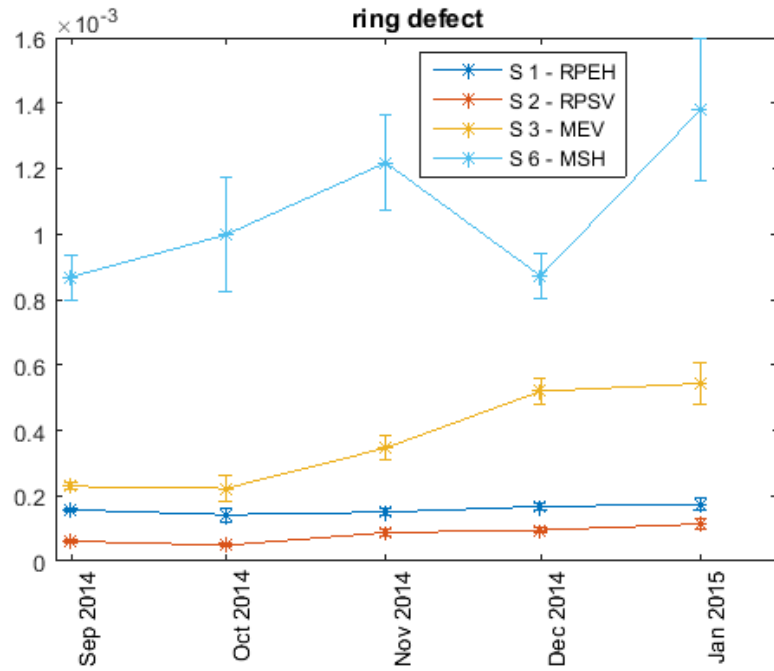


Figure 6.10: Ring defect frequency trend over 5 months monitored by low frequency sensors located on different parts of drive-train.

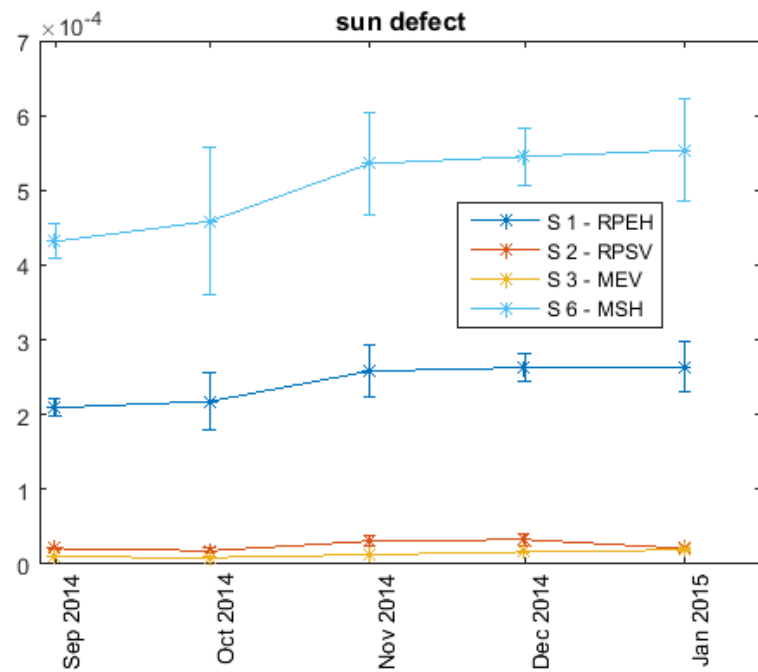


Figure 6.11: Sun defect frequency trend over 5 months monitored by low frequency sensors located on different parts of drive-train.

Table 6.6: The frequencies for the M1 wind turbine generator bearing BB1-7060 B (equivalent to SKF 6330) and the high-speed shaft between gearbox and the generator.

Frequency Name	Frequency at 1100 RPM (Hz)	2 nd harmonic (Hz)	3 rd harmonic (Hz)	4 th harmonic (Hz)
High speed shaft	18.333	36.667	55.000	73.333
Gen. Bearing FTF	7.309	14.618	21.927	29.236
Gen. Bearing BSF	43.374	86.748	130.122	173.497
Gen. Bearing BPFO	65.781	131.561	197.342	263.122
Gen. Bearing BPFI	99.219	198.439	297.658	396.878

As it can be seen in Figure 6.12, the amplitude of the BPFO frequency is relatively low suggesting it is very unlikely that the bearing outer race would be damaged. This can be further confirmed considering the very small amplitude of the 2nd harmonics of this frequency as shown in Figure 6.13. A typical damaged bearing would have at least 10 to 100 times higher amplitudes at the BPFO frequency and its harmonics. It is also noticeable that the signal amplitude has dropped slightly after 31st of May which was due to replacement of the generator bearing carried out.

From the trend analysis shown in Figure 6.12, it can be seen that the amplitude of the generator bearing BPFO frequency is at its highest power on 23rd of May 2016. Looking at the whole spectrum of two radial sensors on the high speed shaft (Figure 6.14)a and the generator (Figure 6.15) on this particular date, it is clearly visible that the generator BPFO frequency is not very significant compared to other frequencies such as high speed shaft or intermediate shaft and the correspondent bearings.

This analysis was later confirmed by inspection of the replaced generator bearing shown in Figure 6.16. The generator bearing was not damaged as predicted by the signal processing performed and reported herewith. Therefore, the replacement had not been necessary and the bearing could have remained in service without cause for immediate concern.

However, looking at the high amplitude of the high-speed shaft frequency and presence of its harmonics it is highly probable that there is a misalignment at the high-speed shaft

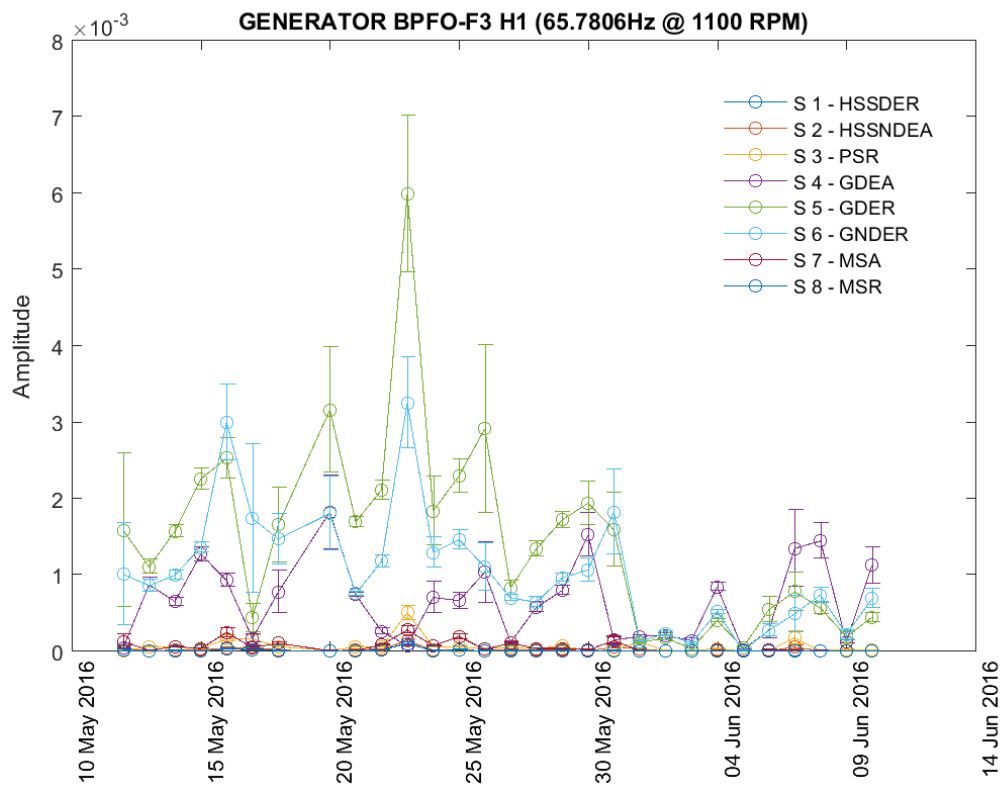


Figure 6.12: Data trend for the generator bearing BPFO frequency recorded by different sensors over one month, averaged on each day.

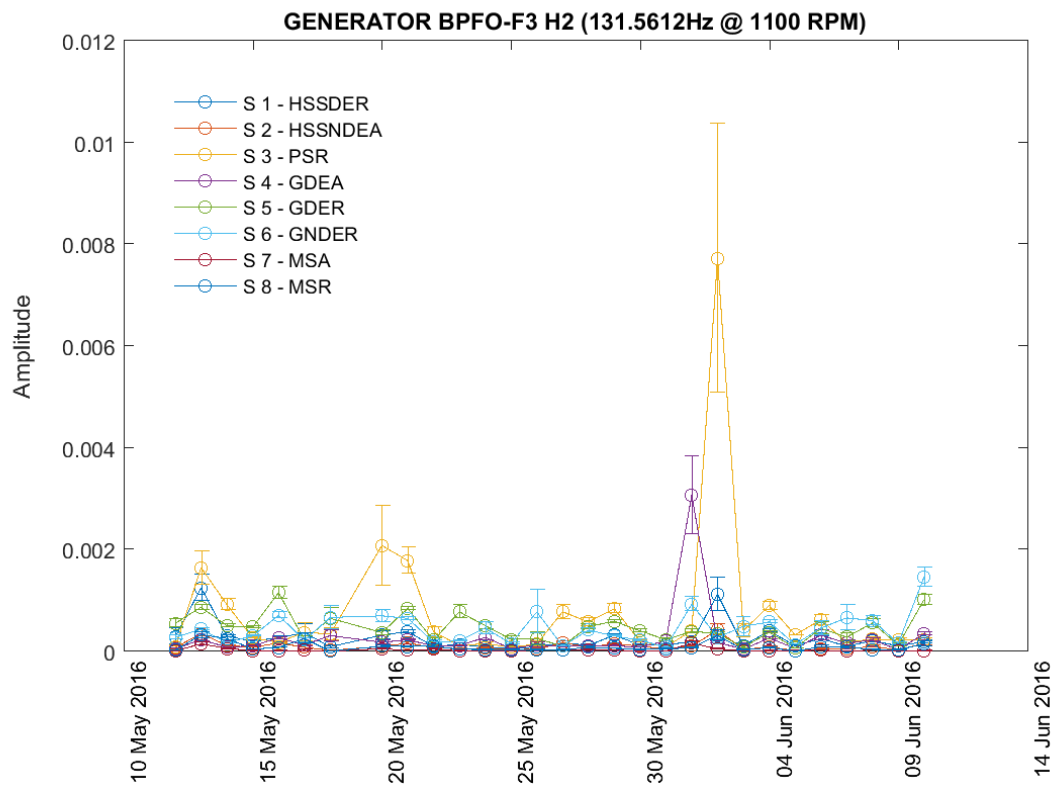


Figure 6.13: Second harmonic data trend for the generator bearing BPFO frequency recorded by different sensors over one month, averaged on each day.

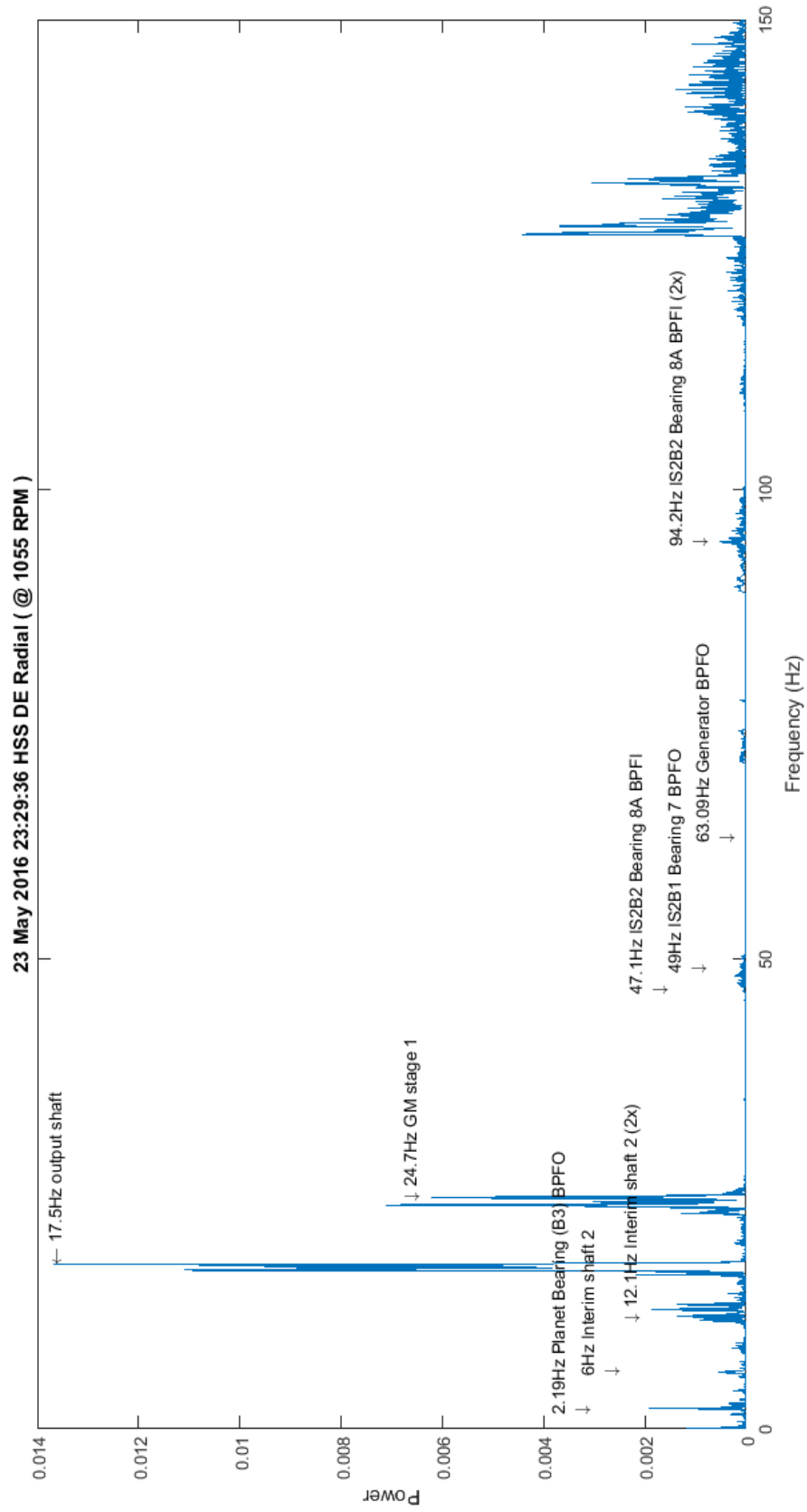


Figure 6.14: The whole spectrum of the data recorded using the radial sensor located at the high speed shaft on 23 May 2016 at 23:29:36 with the wind turbine working near nominal speed of 1100 RPM.

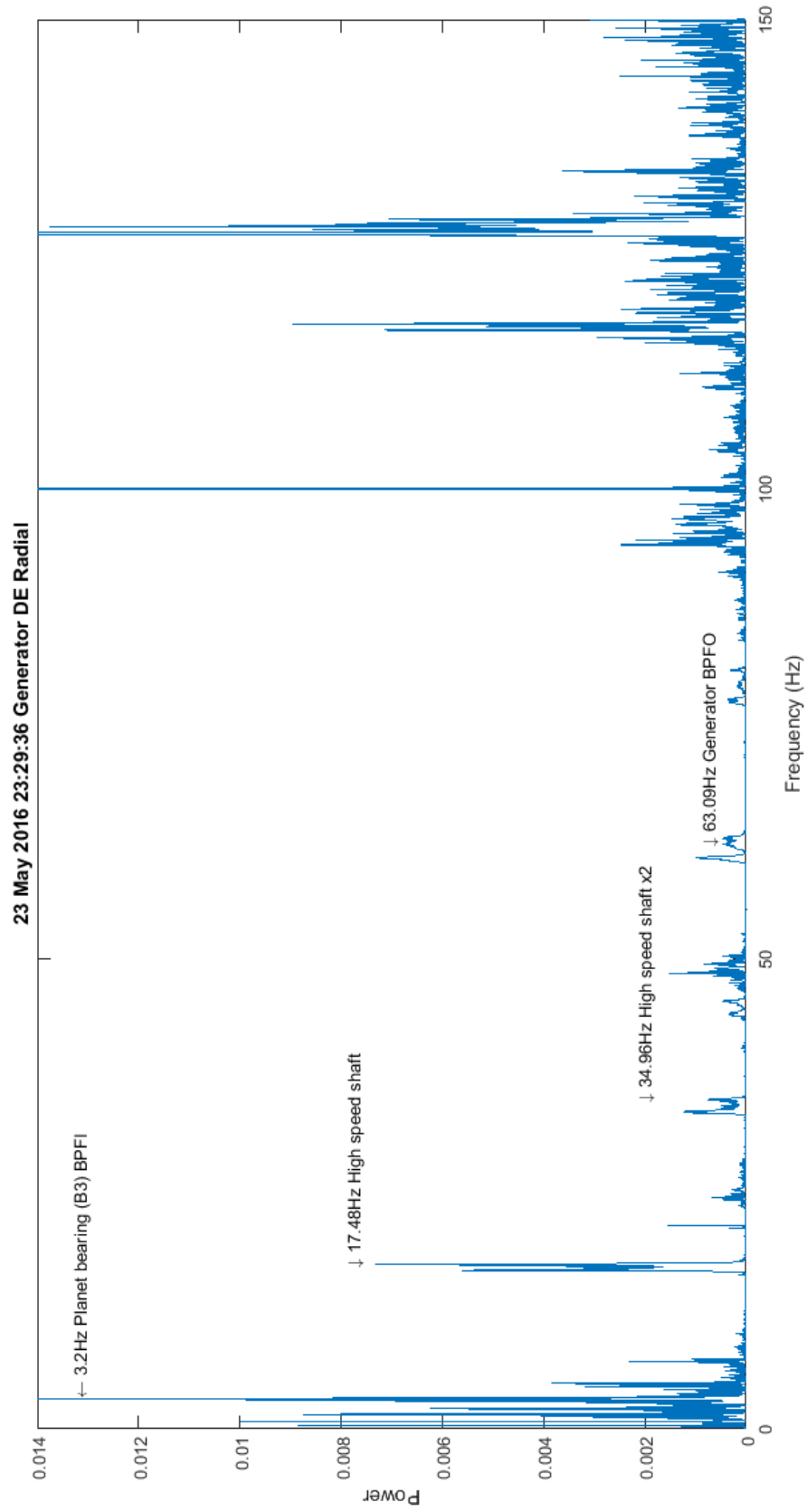


Figure 6.15: The whole spectrum of the data recorded using the radial sensor located at the generator on 23 May 2016 at 23:29:36 with the wind turbine working near nominal speed of 1100 RPM.



Figure 6.16: The removed generator bearing from M1 wind turbine.

as well as an unbalanced load or bent shaft perhaps due to the angular misalignment of the joint. This can be further confirmed by observing a higher amplitude at the high speed shaft frequency measured with the radial sensor and compared with the axial sensor. Figure 6.17 and Figure 6.18 show the high-speed shaft frequency and its second harmonic respectively. As it can be seen, the amplitude of the frequency is considerably high and the vibration intensity recorded with the radial sensor is significantly higher than that recorded by the axial sensor. Similar to the bearing signal, the high-speed shaft frequency power has dropped after 31st of May 2016 which can be due to the maintenance carried out on the wind turbine and partial realignment of the shaft joint.

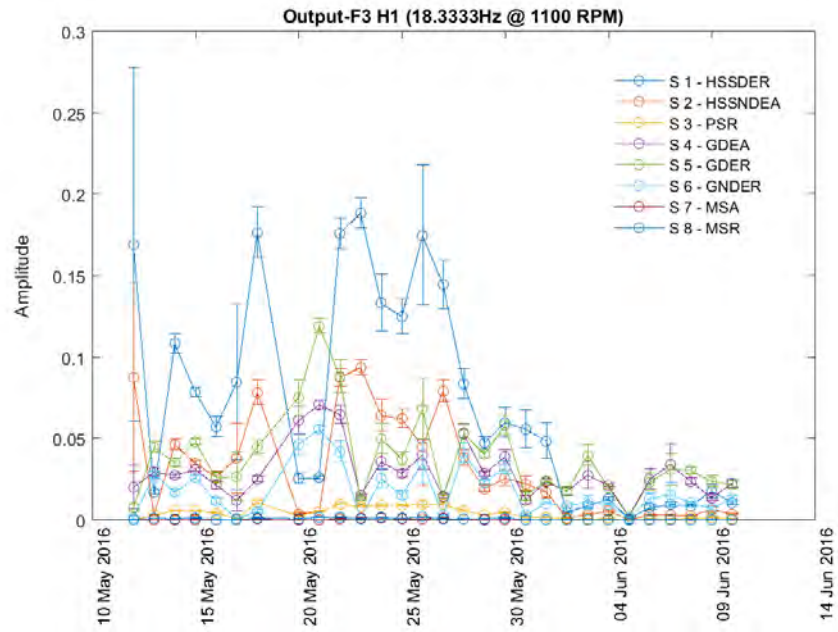


Figure 6.17: Data trend for the high-speed shaft frequency recorded by different sensors over one month, averaged on each day.

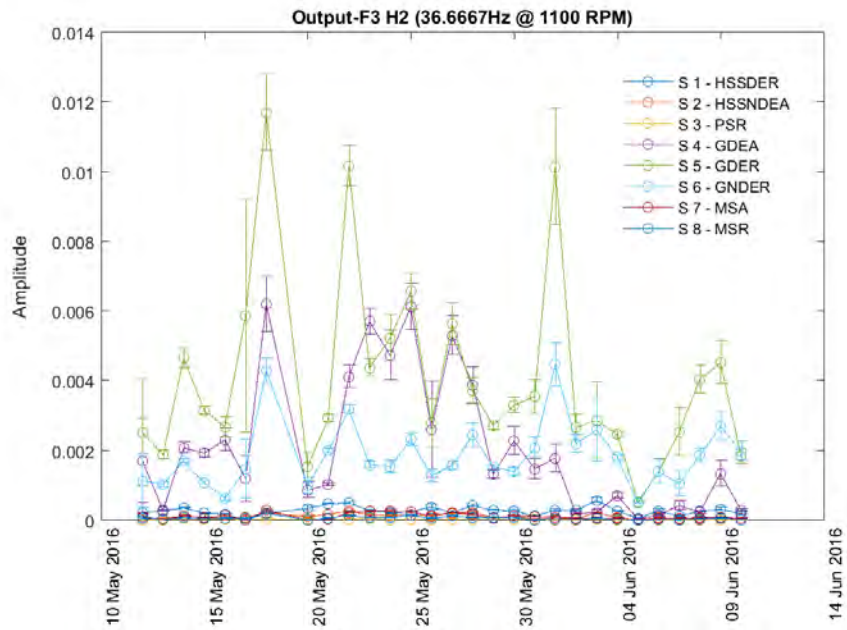


Figure 6.18: Second harmonic data trend for the high-speed shaft frequency recorded by different sensors over one month, averaged on each day.

6.3 Wind turbine M2

6.3.1 Specification

This wind turbine has a lower output capacity in comparison with the M1 wind turbine. Its nominal power capacity is 850kW as shown in Figure 6.19 This turbine was part of a wind farm consisting of 17 wind turbines of the same type with a total nameplate capacity of 14.45MW. This wind turbine has a smaller rotor of 52 metres in diameter and nominal rotational speed of 26.2 RPM. The input from the rotor is connected to a multi-stage planetary gearbox with 1:61.84 ratio with the high speed shaft at the generator turning with a nominal speed of 1620 rpm.

The schematic diagram of the 3-stage gearbox used in the wind turbine M2 is presented in Figure 6.20 along with number of gear teeth, bearing positions and stage ratios. The bearing models corresponding to the numbered positions are listed in Table 6.7 with corresponding defect frequencies calculated using Table 3.5 for 60 RPM rotational speed at the output or high speed shaft of the gearbox (i.e. generator).

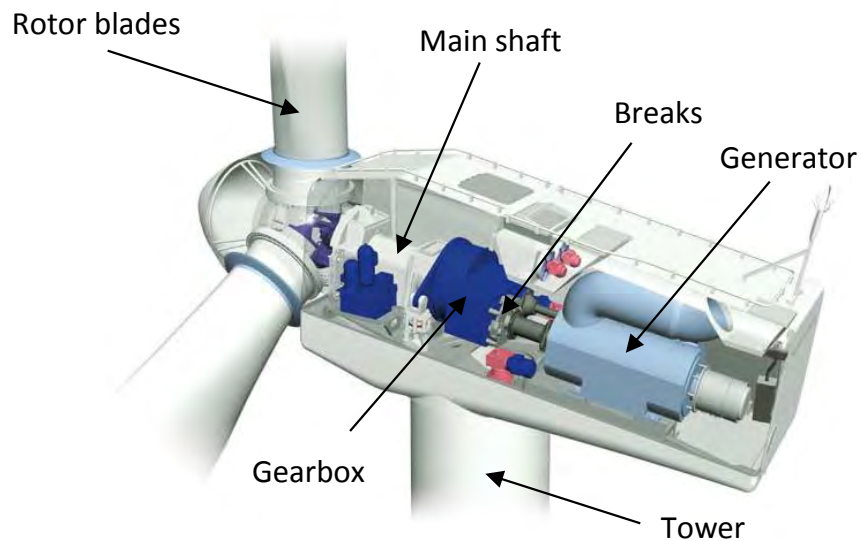


Figure 6.19: The instrumented wind turbine M2

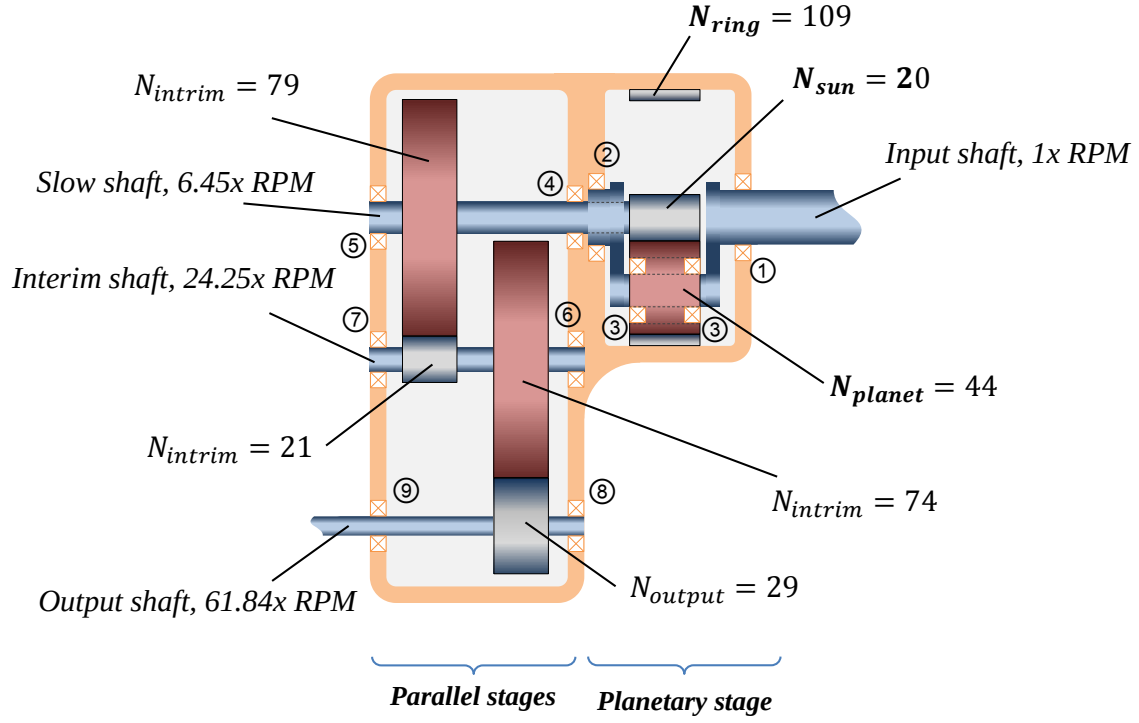


Figure 6.20: The gearbox used in wind turbine M2.

Table 6.7: The bearing frequencies calculated in Hertz for the wind turbine M2 with 60 rpm (1 order) speed at generator

Position No.	Model	FTF	BSF	BPFO	BPFI
1	BT1-8041	N.A.	N.A.	N.A.	N.A.
2	LM 757010	0.008	0.130	0.357	0.402
3 (X6)	NJ2330 ECMA C3	0.023	0.143	0.319	0.467
4	NJ2956/C3/PEX	0.048	0.612	1.764	2.090
5 (x2)	32944	0.048	0.673	1.833	2.126
6	NU2328 EJ	0.159	0.999	2.224	3.262
7	31322X	0.162	0.957	2.590	3.680
7	30322	0.159	0.998	2.551	3.720
8	NU2218EJ/C3	0.425	3.240	7.218	9.782
9	71750	0.444	4.296	10.220	12.780
9	HM926710	0.435	3.490	8.703	11.300

6.3.2 Instrumentation

The instrumentation of the wind turbine drive-train was carried out by Ingeteam Service. INGETEAM Service is a Spanish company with headquarters in Pamplona, Spain. In order to measure vibrations in the drive train, 8 piezoelectric sensors have been used, two of them specifically selected to measure low frequencies at the main shaft. The choice of sensor selection were based on the frequency range of interest at each stage of the gearbox. For example, the low speed shaft and the planetary stage gears produce significantly lower range of frequencies in comparison with the high-speed shaft. The summary of the used sensors is tabulated in Table 6.8.

Table 6.8: Summary of installed sensors along the wind turbine drive-train including their name, model and location

Model	Sensitivity	Range	Measurment range	Mounting	Picture
PRE-1010-MS	100 mV/g	0.5 Hz to 10000 Hz	$\pm 50g$	Military Standard 2-Pin	
PRE-1030-MS	500 mV/g	2 Hz to 10000 Hz	$\pm 80g$	Military Standard 2-Pin	

The location of each sensor on the drive-train is shown in the schematic diagram in Figure 6.21. Details are listed in Table 6.9. The sensors are fixed in place using epoxy adhesive directly on the body of the wind turbine drive-train as shown in Figure 6.22.

The installed sensors were connected to INGESYS CMS data acquisition unit which has been developed by Ingeteam Company and it is shown in Figure 6.23.

Each sensor was sampled and filtered with different frequency range and sampling rate

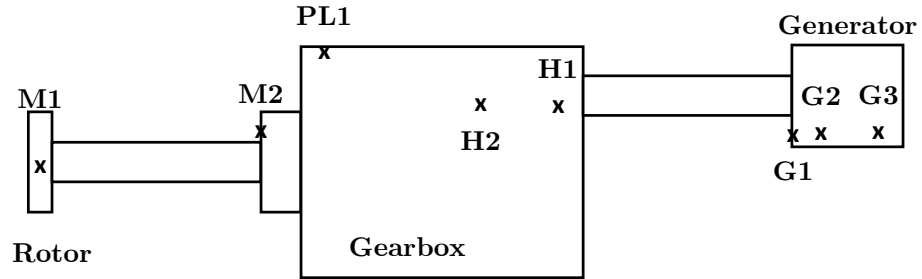


Figure 6.21: Instrumentation of the drive train of M2 wind turbine by INTEGEM.

Table 6.9: Summary of installed sensors along the wind turbine drive-train including their name, model and location

Sensor	Signal	Model	Deirection	Location
M1	MSR	PRE-1010-MS	Radial	Main bearing (back)
M2	MSA	PRE-1010-MS	Axial	Main bearing (front)
PL1	PLR	PRE-1030-MS	Radial	Planetary gears (Low speed)
H1	HSS-DE-R	PRE-1030-MS	Radial	High speed bearing (Drive End)
H2	HSS-NDE-R	PRE-1030-MS	Radil	High speed bearing (Non-Drive End)
G1	GEN-DE-A	PRE-1030-MS	Axial	Generator (Drive End)
G2	GEN-DE-R	PRE-1030-MS	Radial	Generator (Drive End)
G3	GEN-NDE-R	PRE-1030-MS	Radial	Generator (Non-Drive End)



Figure 6.22: Installed sensor on the wind turbine M2; top: Generator Drive End Radial and Axial sensors, bottom: Planetary Radial Sensor (Photographs are courtesy of Ingeteam).



Figure 6.23: Ingesys CMS system located in nacelle containing Data acquisition, communication and power unit (Photograph is courtesy of Ingeteam).

to get maximum information from different frequency bands. These frequency bands are listed in Table 6.10.

Table 6.10: Applied digital filter on the recorded data from M2 drive-train acquired by Ingeteam

Filter number	Lower frequency (Hz)	Top frequency (Hz)	Frequency Resolution (Hz)	Truncation (number of samples)	Final sample frequency (Hz)
F1	0	750	0.046	16384	750
F2	0	1280	0.183	8192	1500
F3	0	1500	0.092	16384	1500
F4	0	20400	2.930	8192	24000
F5	0	51200	5.859	8192	48000

6.3.3 Data analysis

The original recorded data files are in ASCII format and have been converted to MATLAB compatible format. The converted data files were then analysed for presence of any defect frequency which are calculated using the equations listed in Table 3.3 and Table 3.5 each instance using the relevant wind turbine blade speed. Table 6.11 presents these frequencies calculated for the nominal speed of 1620 RPM at high speed shaft. The presence and variation of these frequencies has been investigated over several months to obtain the trends in these interested frequencies.

This wind turbine had more wear than the previous wind turbine and was suspected to have some damage at the low speed stages i.e. planetary side. Data analysis performed on the vibration signal recorded from the wind turbine indubitably confirmed the damage at the planetary stage.

Figure 6.24 shows the time signal and corresponding spectrum from the sensor installed near the planetary stage of the gearbox. As it can be seen the gear mesh frequency is dominating the signal, however looking at the low frequency spectrum in Figure 6.25 the planetary gear frequencies and corresponding defect frequencies are visible. The planetary

Table 6.11: M2 Gearbox frequencies based on 1620 rpm nominal output

Parameter	RPM	Hz
High speed shaft (output)	1620	27
Speed		
Interim shaft 2 speed	634.86	10.58
Interim shaft 1 speed	168.76	2.81
Input shaft speed	26.16	0.44
Planet	64.82	1.08
Gear Mesh		
GM Stage 3	46980	783
GM Stage 2	13332.16	222.20
GM Stage 1	2851.94	47.53
GM planet	8555.82	142.60
Defect Frequencies		
Sun gear	427.79	7.13
Ring gear	78.49	1.31
Planetary gear	129.63	2.16

bearing BPFO is also noticeable and low speed shaft and bearings frequencies are also present that indicates degradation and damage to the planetary stage of the gearbox.

The acoustic emission signal recorded from the gearbox by the University of Birmingham was also confirming this defect by showing similar results. The recorded acoustic emission data is presented in Figure 6.26 with the corresponding frequency spectrum. This data was demodulated using enveloping technique and the result is shown in Figure 6.27. The presence of modulated planetary gear mesh with side-bands and peaks at harmonics frequency indicate damage to the planets.

Filtering and demodulating the signal using spectrogram technique yields similar conclusions as the other techniques. Figure 6.28 shows the performed Kurtogram on the signal identifying the centre frequency and the bandwidth with maximum kurtosis.

Using the information obtained from the Kurtogram analysis, the signal was demod-

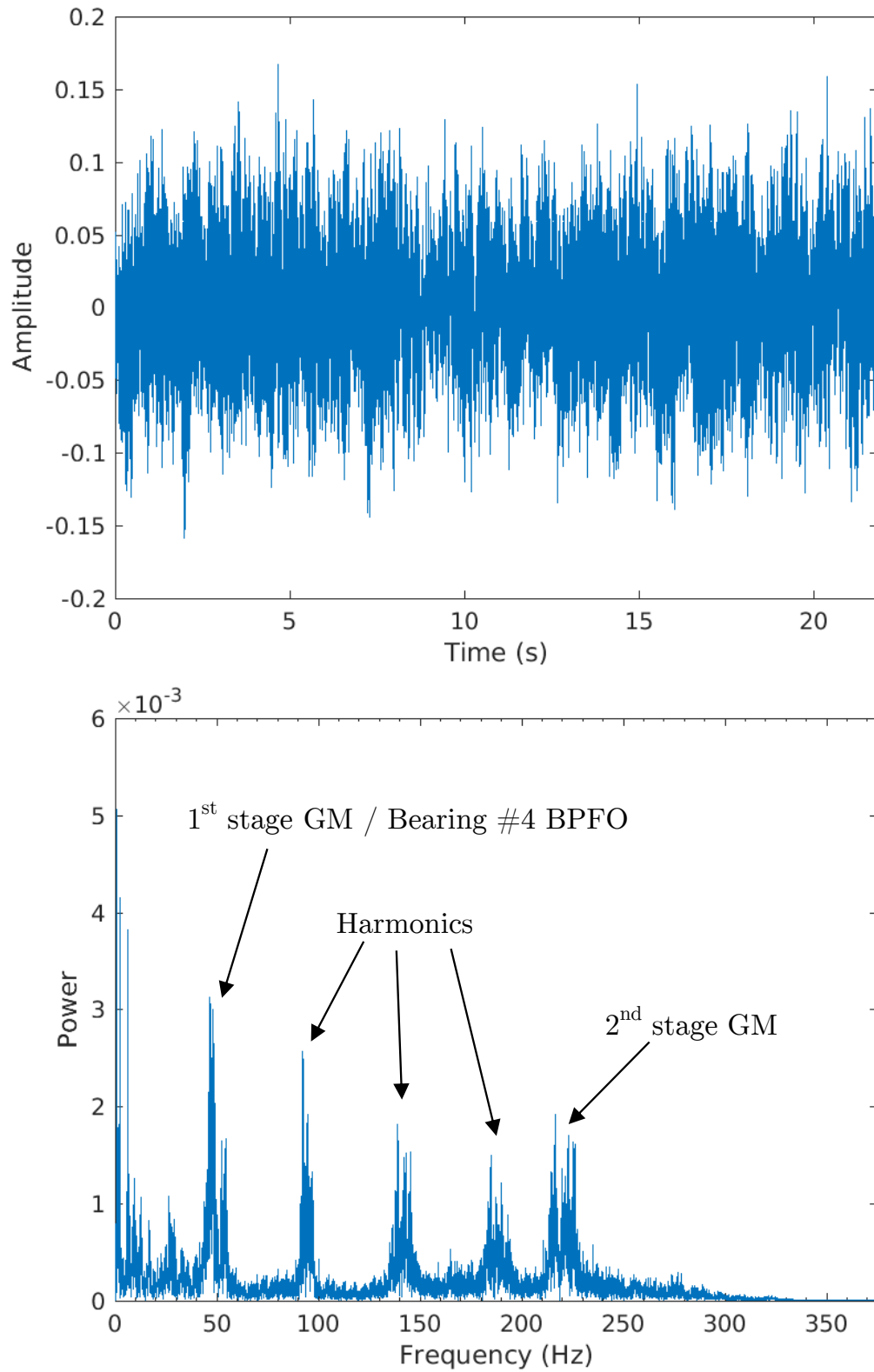


Figure 6.24: Vibration time signal (top) and corresponding spectrum (bottom) from planetary stage sensor PL1 with F1 filter.

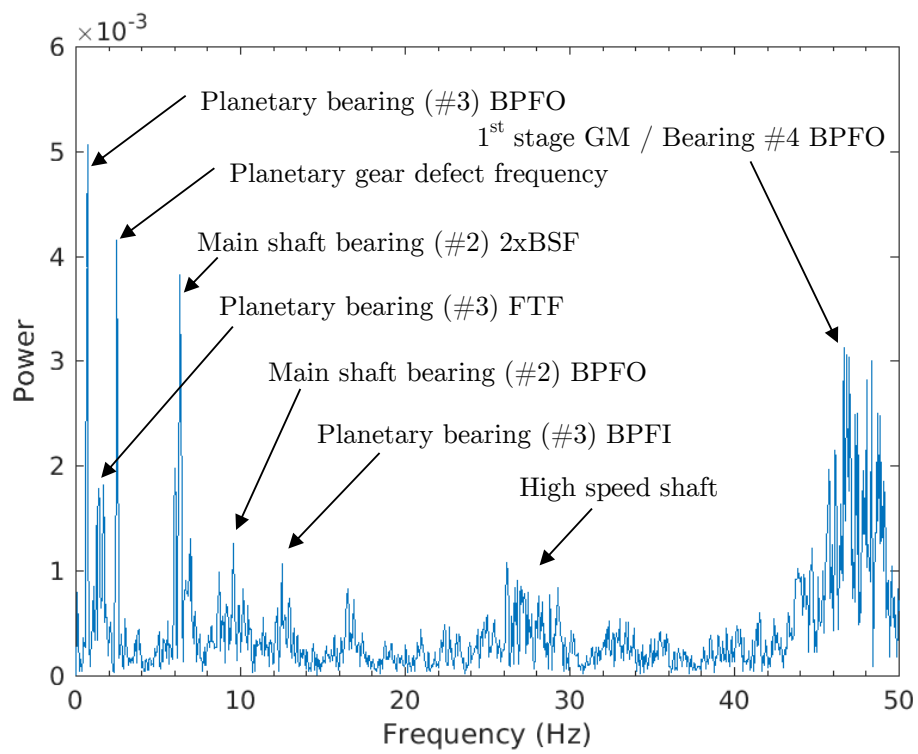


Figure 6.25: Low frequency spectrum of the vibration signal recorded from planetary stage sensor PL1 with F1 filter.

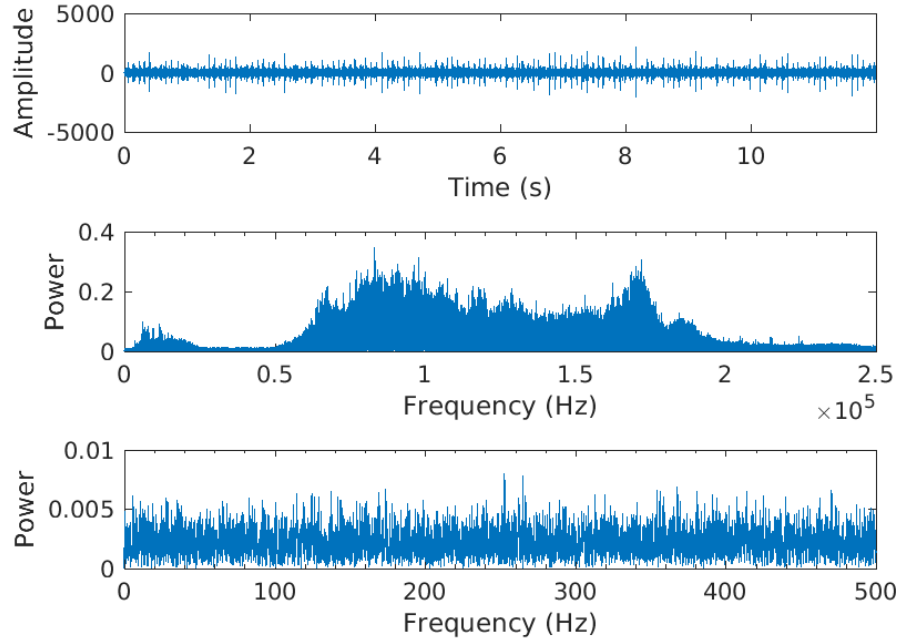


Figure 6.26: Data recorded using Acoustic emission sensor near the planetary stage. Top: raw signal, middle: calculated spectrum, bottom: zoomed spectrum.

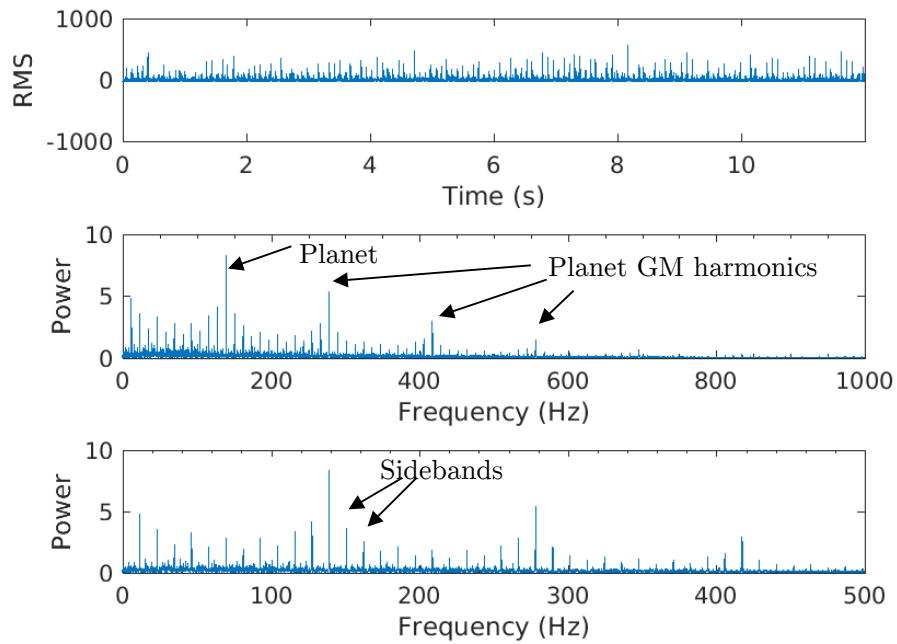


Figure 6.27: Demodulated Acoustic emission data from planetary stage using enveloping technique. Top: demodulated signal, middle: calculated spectrum, bottom: zoomed spectrum.

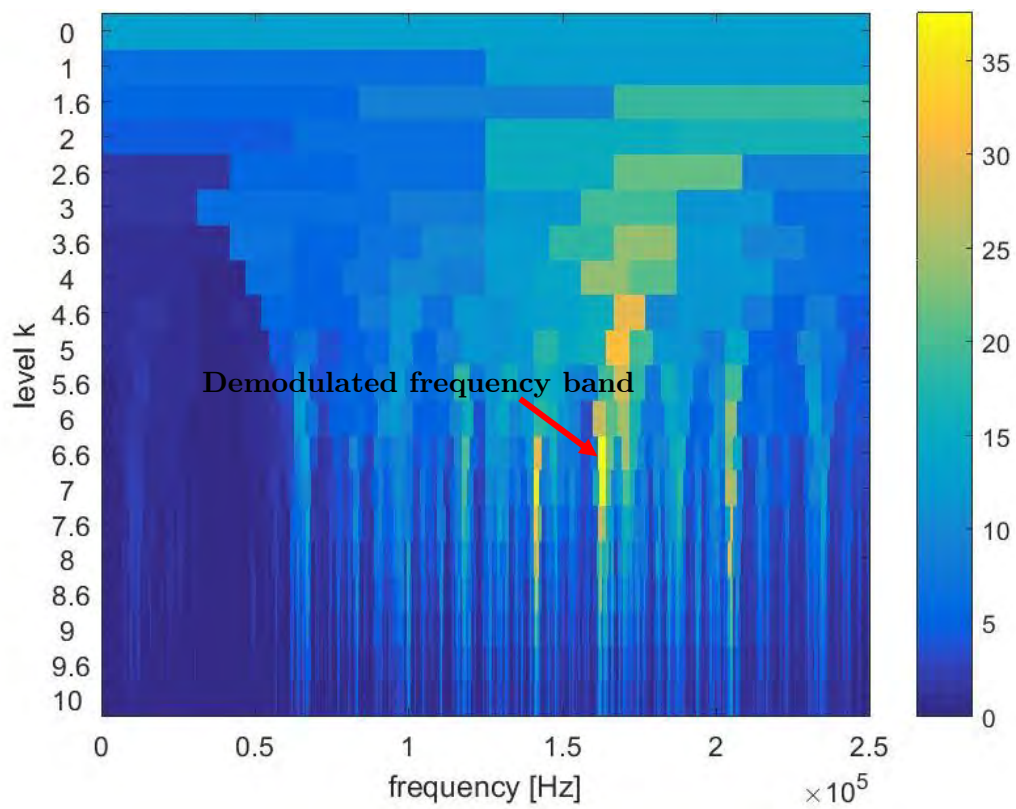


Figure 6.28: Kurtogram performed on the acoustic emission signal, showing maximum kurtosis of 37.6 at level 6.5 corresponding to centre frequency of 162.76 kHz and a band-width of 2604Hz.

ulated and filtered. The final result is shown in Figure 6.29.

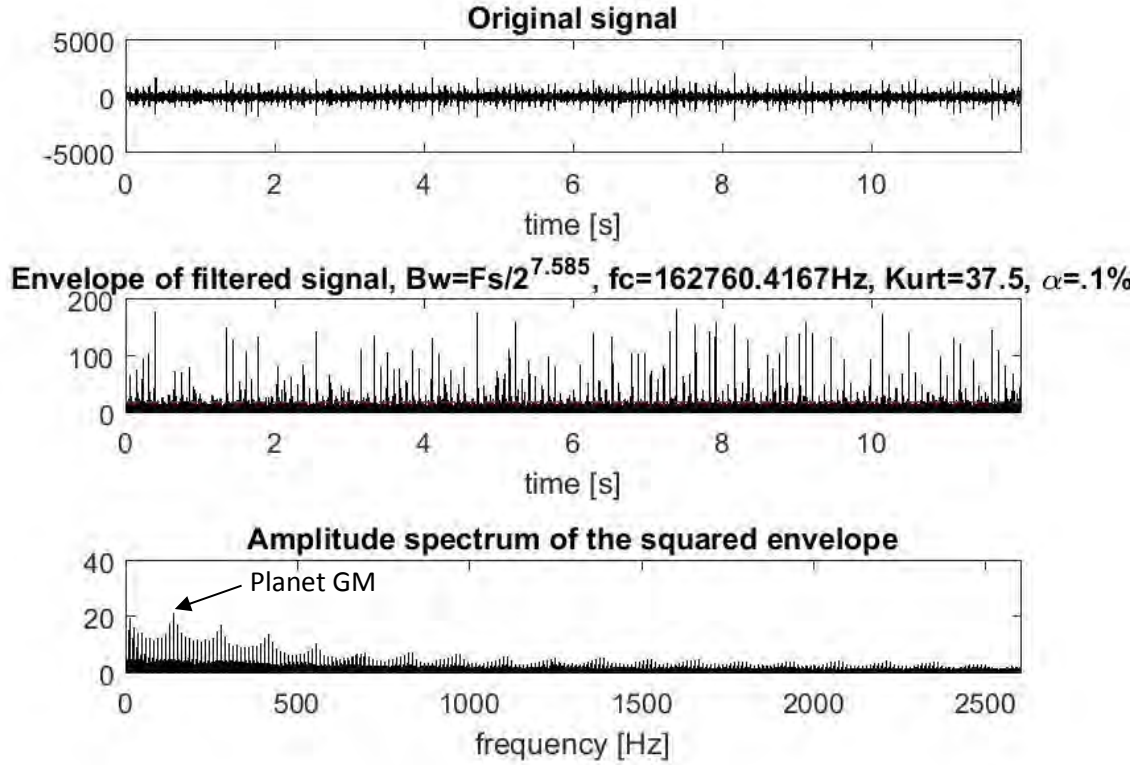


Figure 6.29: Demodulated acoustic signal using Kurtogram. Top: original signal, middle: signal envelope, bottom: signal spectrum.

Performing the time and spectral kurtosis on the data is also showing the defect in the system. The high value of kurtosis as can be seen in Figure 6.30 (top), suggests that the system is not running smoothly and the signal is very spiky. Similarly, the spectral kurtosis shows a constant peak at planetary gear mesh with side-band that indicates damaged planetary stage. This is shown in Figure 6.30 (bottom) For comparison purposes, the corresponding time and spectral kurtosis from M1 wind turbine that was discussed earlier is presented in Figure 6.31. As it can be seen, the overall value of the time kurtosis and short window moving kurtosis both remain below 3 that indicates a very smooth and non-spiky signal. Similarly, the spectral kurtosis is very flat with peaks below 2 that is considerably smaller than M2 wind turbine with peaks as high as 2×10^7 .

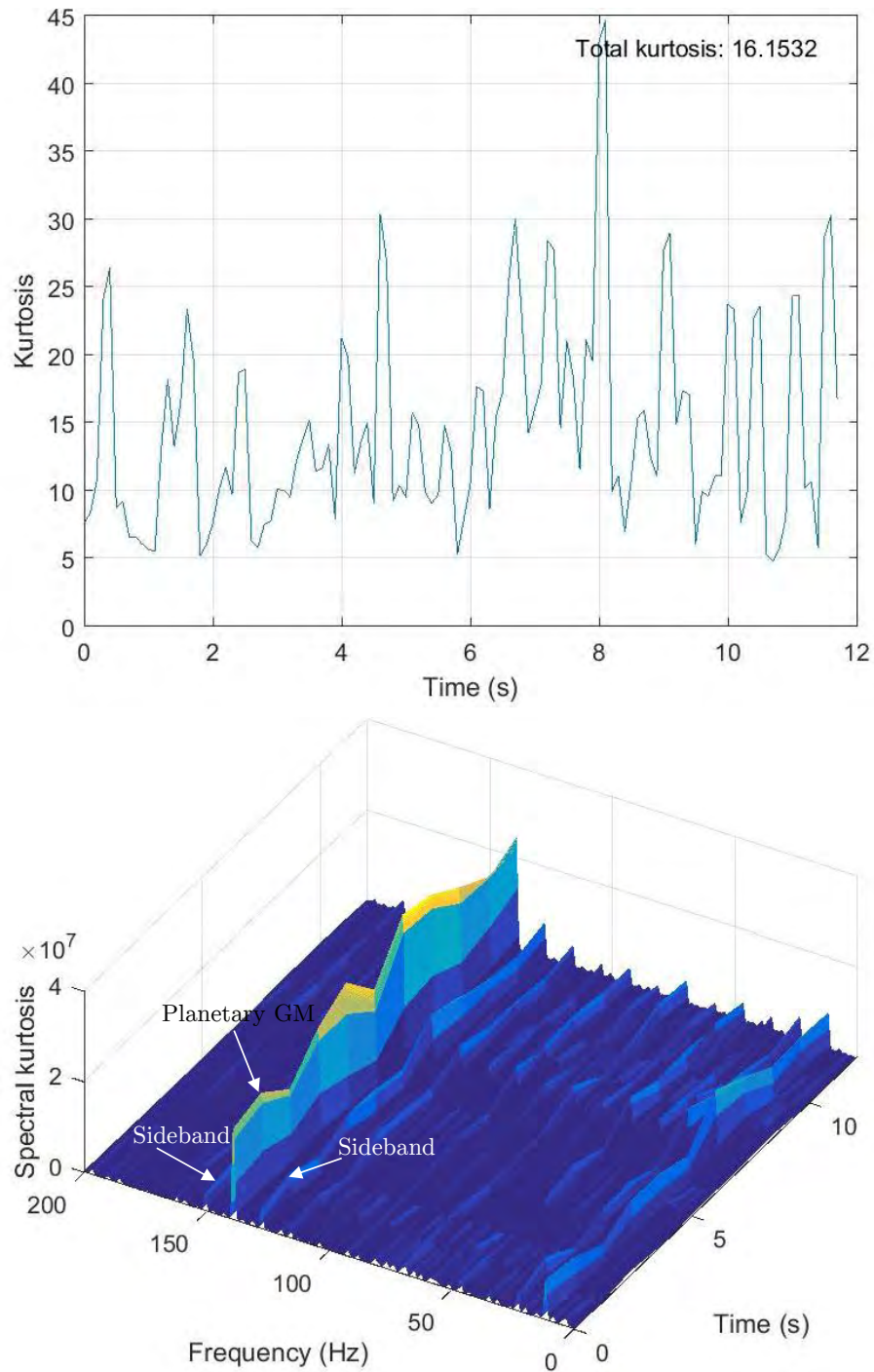


Figure 6.30: Acoustic signal kurtosis analysis performed on time signal of M2 wind turbine with 200ms windowing on top and spectral kurtosis with 1ms RMS window and 1s FFT window on bottom.

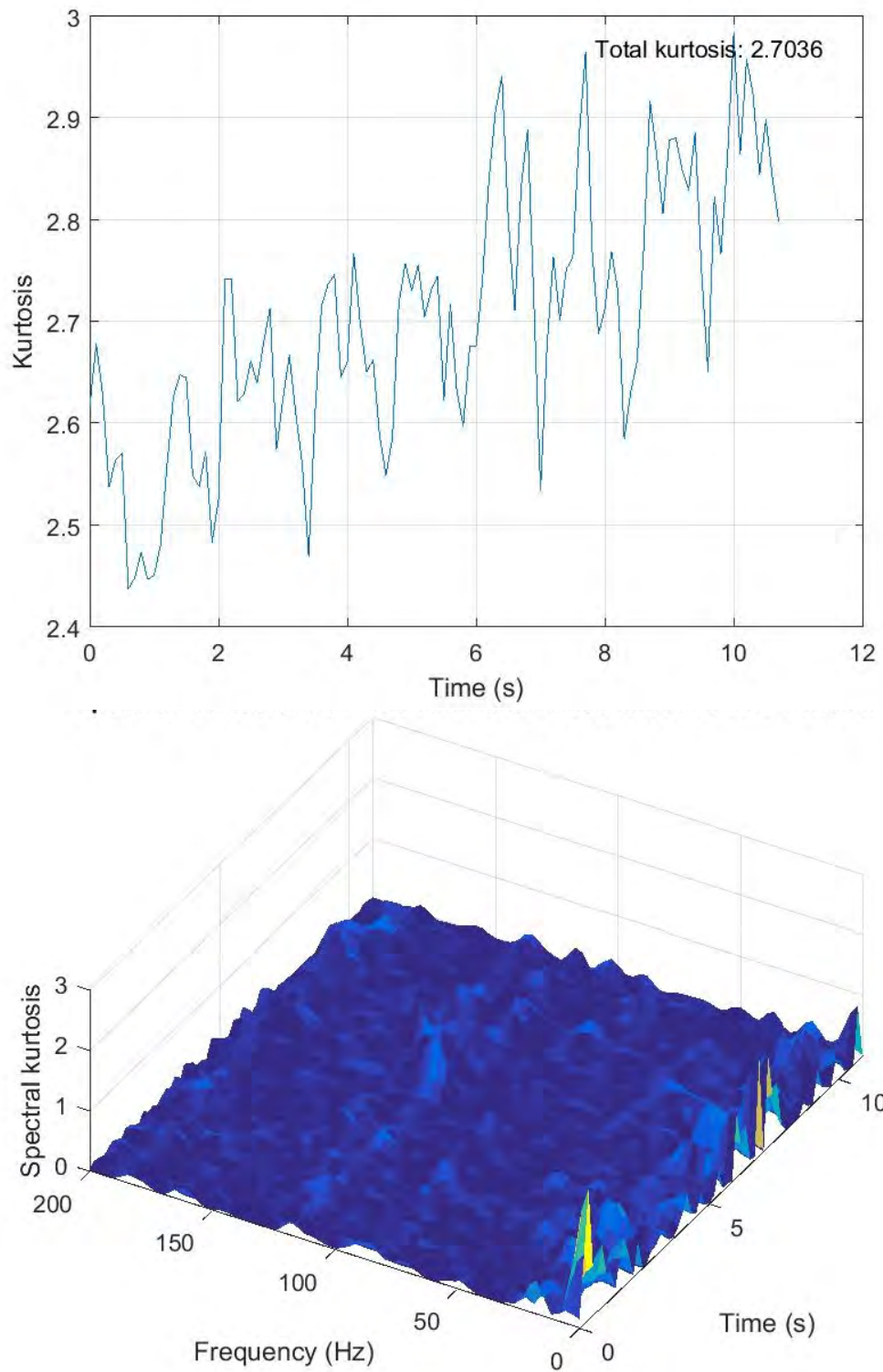


Figure 6.31: Acoustic signal kurtosis analysis performed on time signal of M1 wind turbine with 200ms windowing on top and spectral kurtosis with 1ms RMS window and 1s FFT window.

6.4 Wind turbine M3

6.4.1 Specification

This wind turbine is a relatively small one compared with the previous wind turbines having a nominal output power of 600kW. The wind turbine M3 is illustrated in Figure 6.32. The rotor diameter of this wind turbine is 43 metre and the nominal rotor speed is 27.4 rpm. Similar to the previous wind turbines, the rotor is connected to a multi stage planetary gearbox with a ratio of 1:55.11 and a nominal speed of 1510 rpm at the generator. The rotor rather than having pitch-control blades, employs a stall design which allows the wind turbine to brake aerodynamically above a certain wind speed. Stall rotor designs have been abandoned in modern larger units, employing exclusively pitch-control blades.

The schematic diagram of the 3-stage gear train used in wind turbine M3 is presented in Figure 6.32 along with the number of gear teeth, bearing positions and stage ratios. The bearing models corresponding to the numbered positions are listed in Table 6-12 with corresponding defect frequencies calculated using Table 3-5 for 60 rpm speed at the output or high speed shaft of the gearbox (i.e. generator).

Table 6.12: The bearing frequencies calculated in Hertz for the wind turbine M3 with 60 rpm (1 order) speed at generator

Position	Model	FTF	BSF	BPFO	BPMF
Input shaft	N.D.	0.008	0.338	0.504	0.561
Input shaft	N.D.	0.008	0.321	0.447	0.534
Planets (X6)	N.D.	0.021	0.358	0.411	0.529
Sun shaft	N.D.	0.035	0.513	0.416	0.570
Sun shaft	N.D.	0.047	1.911	2.847	3.161
Sun shaft	N.D.	0.044	0.703	0.828	1.100
LSS	N.D.	51200	0.172	2.921	3.979
LSS	N.D.	51200	0.165	2.309	3.373
HSS	N.D.	51200	0.423	7.197	9.803
HSS	N.D.	51200	0.423	7.197	9.804

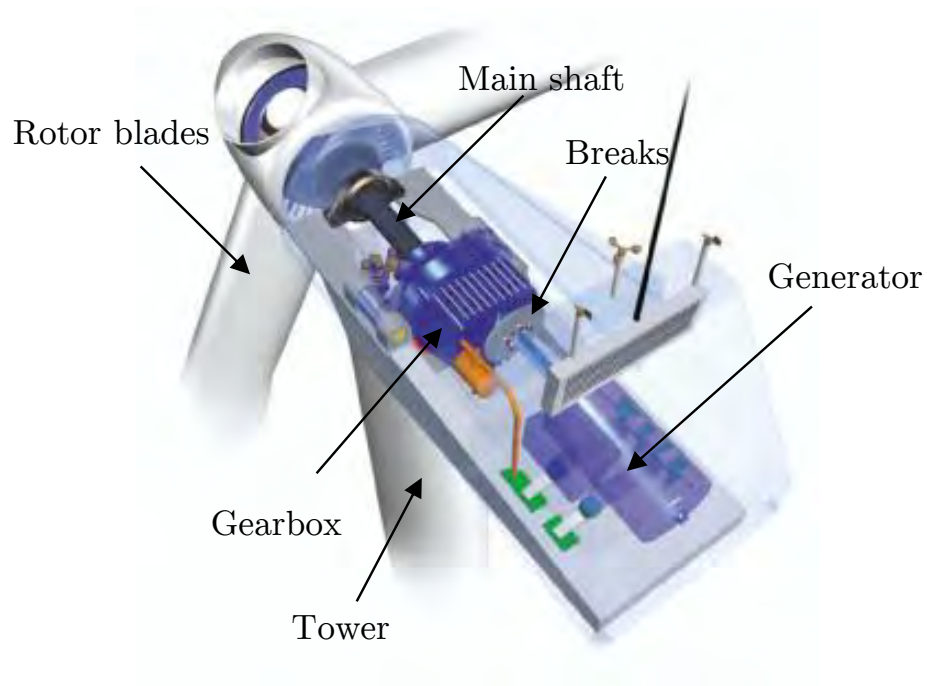


Figure 6.32: The instrumented wind turbine M3.

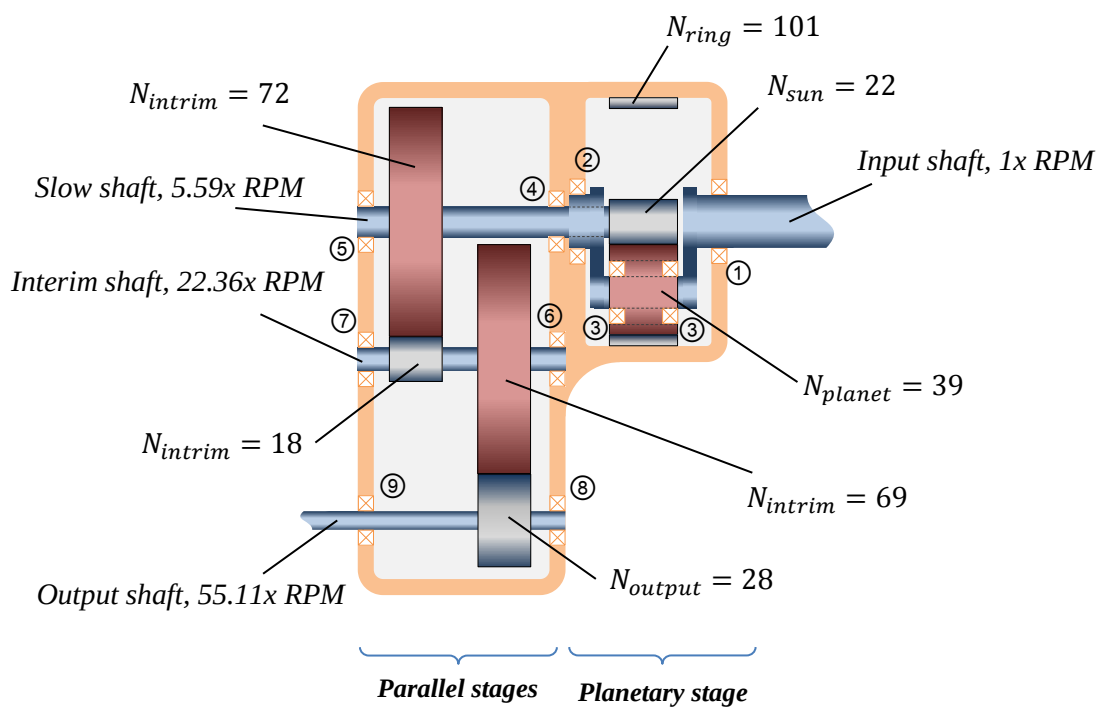


Figure 6.33: The gearbox used in wind turbine M3.

6.4.2 Instrumentation

The instrumentation of the M3 wind turbine drive-train was performed by the University of Birmingham using acoustic emission sensors. Unlike the other wind turbines where sensors were installed permanently, the instrumentation of the wind turbine was performed temporarily using magnetic hold-downs.

The AE sensors used were R50 α resonant piezoelectric sensors procured from Physical Acoustics Corporation (now Mistras) with a peak sensitivity of 62dB and operational frequency range of 100-700 kHz. The data acquisition unit was a digital Agilent U2531A USB DAQ with 14bits resolution and a maximum shared sampling rate of 2MSamples/s.

Each sensor was sampled at 500kSamples/s for a duration of 12 seconds. A total of 40 recordings over a period of 1 hour was performed. Unlike the other wind turbines that were monitored over a long period of time, these measurements provided a few snapshots in time to analyse the gearbox condition and identify any damage present.

6.4.3 Data analysis

The recorded acoustic data files were in national instrument technical data management solution (TDMS) format and have been converted to MATLAB compatible format. The converted data files were then analysed for presence of any defect frequency which are calculated using the equations listed in Table 3.3 and Table 3.5 at each instance using the relevant wind turbine blade speed. Table 6.13 presents these frequencies calculated for the nominal speed of 1510 RPM at high speed shaft.

Unlike the other two wind turbines, this wind turbine had various unidentified wear and damages. The recorded acoustic data was investigated using various techniques to identify any possible damage in the wind turbine.

First, the time signal and demodulated signal were investigated. Figure 6.34 shows the signal recorded at the low speed shaft. As it can be seen, there are several peaks in the signal that shows the possibility of a fault being present in that area. Looking at signal

Table 6.13: M3 Gearbox frequencies based on 1510 rpm nominal output

Parameter	RPM	Hz
High speed shaft (output)	1510	25.17
Speed		
Interim shaft 2 speed	612.75	10.21
Interim shaft 1 speed	153.19	2.55
Input shaft speed	27.40	0.46
Planet	70.96	1.18
Gear Mesh		
GM Stage 3	42280	704.67
GM Stage 2	11029.60	183.83
GM Stage 1	2767.35	46.12
GM planet	8302.06	138.37
Defect Frequencies		
Sun gear	377.37	6.29
Ring gear	82.20	1.37
Planetary gear	141.92	2.37

recorded at the planetary stage, it has a very spiky nature compared to the input stage as shown in Figure 6.35. However, moving further to the intermediate shaft and high speed shaft region, the signal become quieter as shown in Figure 6.36 and Figure 6.37 respectively. This suggests that the problem is more local at the slow speed and planetary stage of the gearbox. This also can clearly be seen from the short time Fourier transform performed on the signal (Figure 6.38) The fault amplitude is smaller at the main shaft region and peaks at planetary region while it is absent from the signals recorded at intermediate and high speed shaft regions.

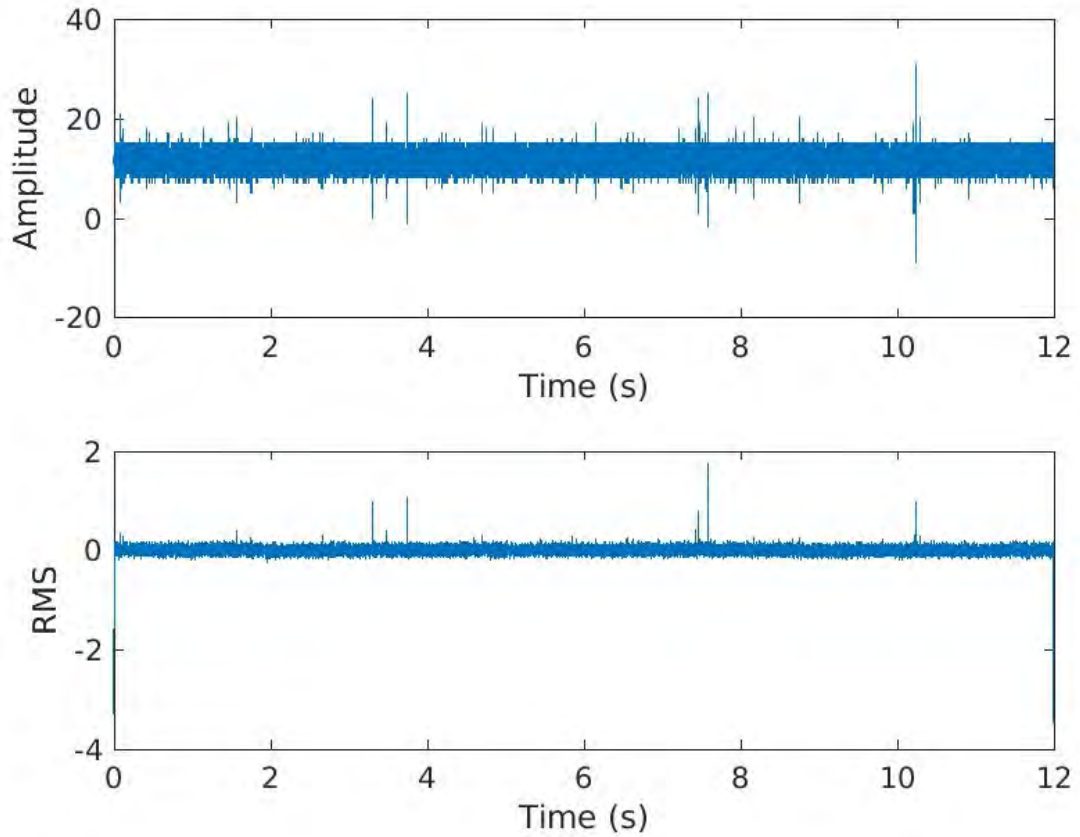


Figure 6.34: The time and corresponding RMS signal recorded from gearbox of M3 wind turbine with the acoustic sensor located at the main shaft.

Spectral kurtosis analysis of the signal is also suggesting the same results as the previous techniques. Figure 6.39 and Figure 6.40 show the calculated spectral kurtosis for low speed and high-speed regions of the gearbox respectively.

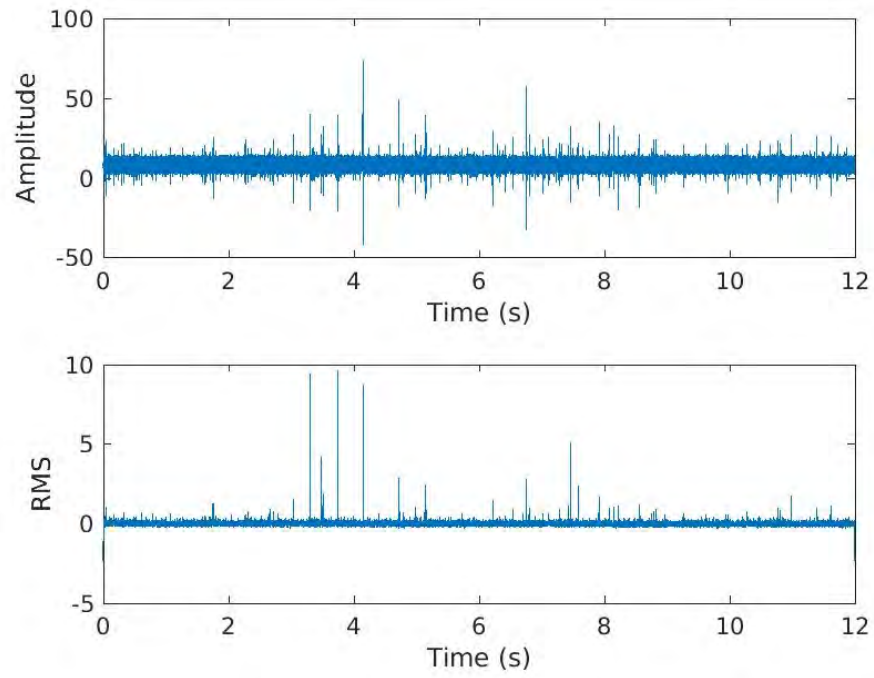


Figure 6.35: The time and corresponding RMS signal recorded from gearbox of M3 wind turbine with the acoustic sensor located at the planetary stage.

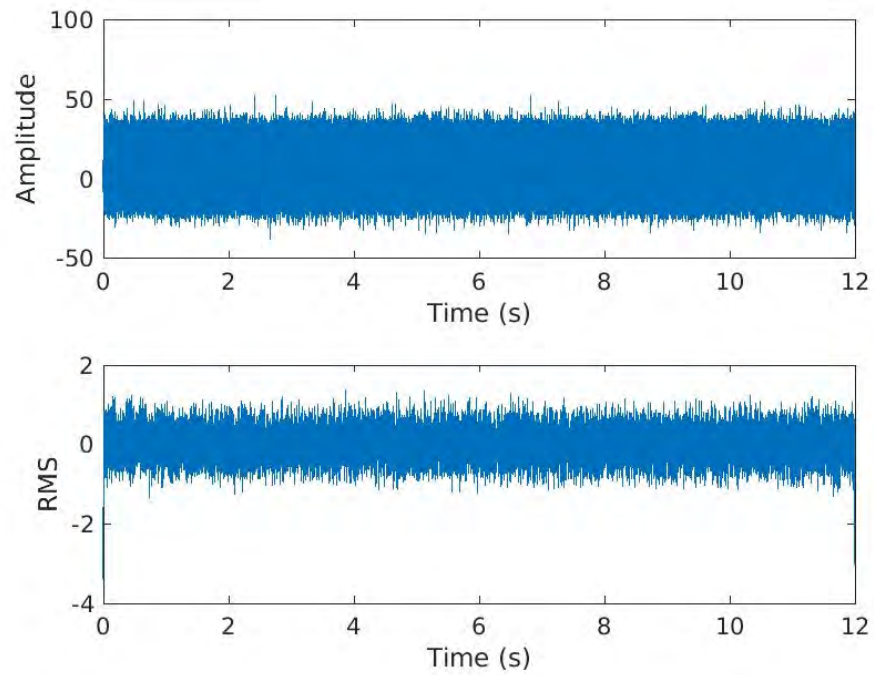


Figure 6.36: The time and corresponding RMS signal recorded from gearbox of M3 wind turbine with the acoustic sensor located at the interim shafts

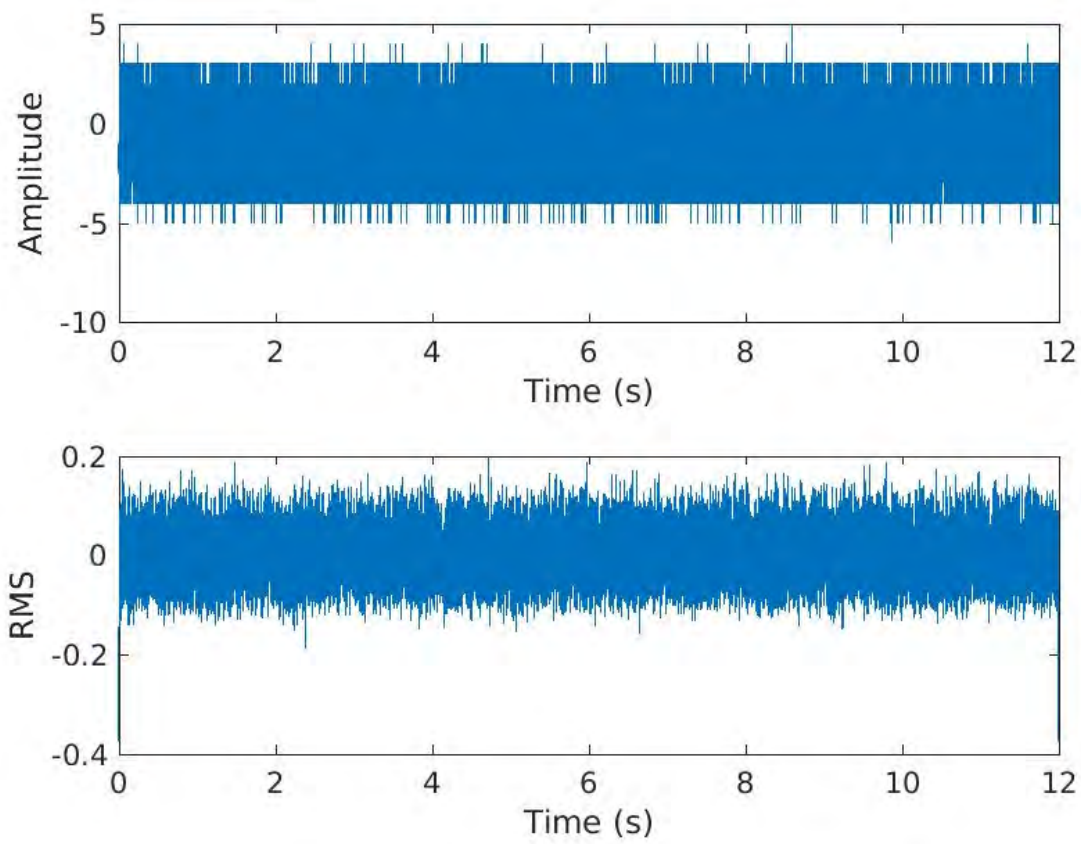


Figure 6.37: The time and corresponding RMS signal recorded from gearbox of M3 wind turbine with the acoustic sensor located at the high-speed shaft

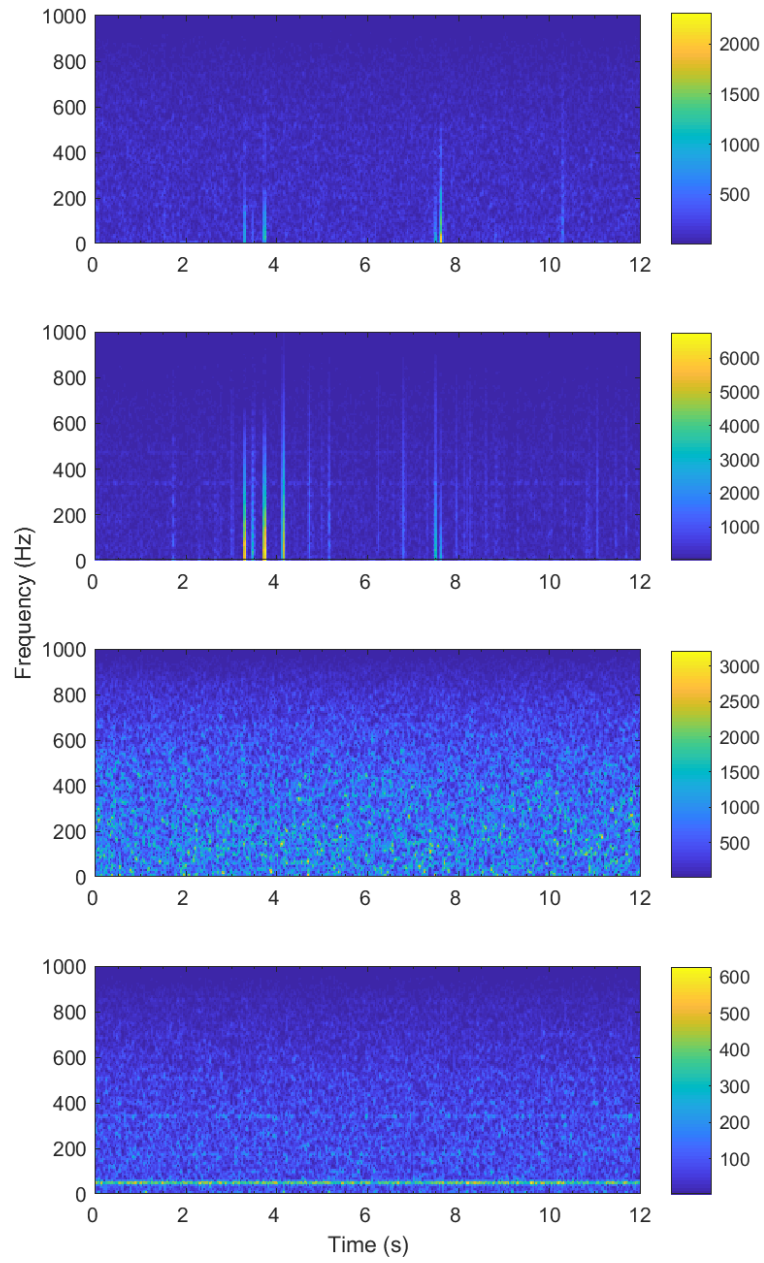


Figure 6.38: Short time Fourier transform of signal recorded from gearbox of M3 wind turbine with the acoustic sensor with 100ms FFT window. From top to bottom: input shaft, planetary, interim, high speed shaft regions

Spectral Kurtosis with 1ms RMS and ~1s FFT window

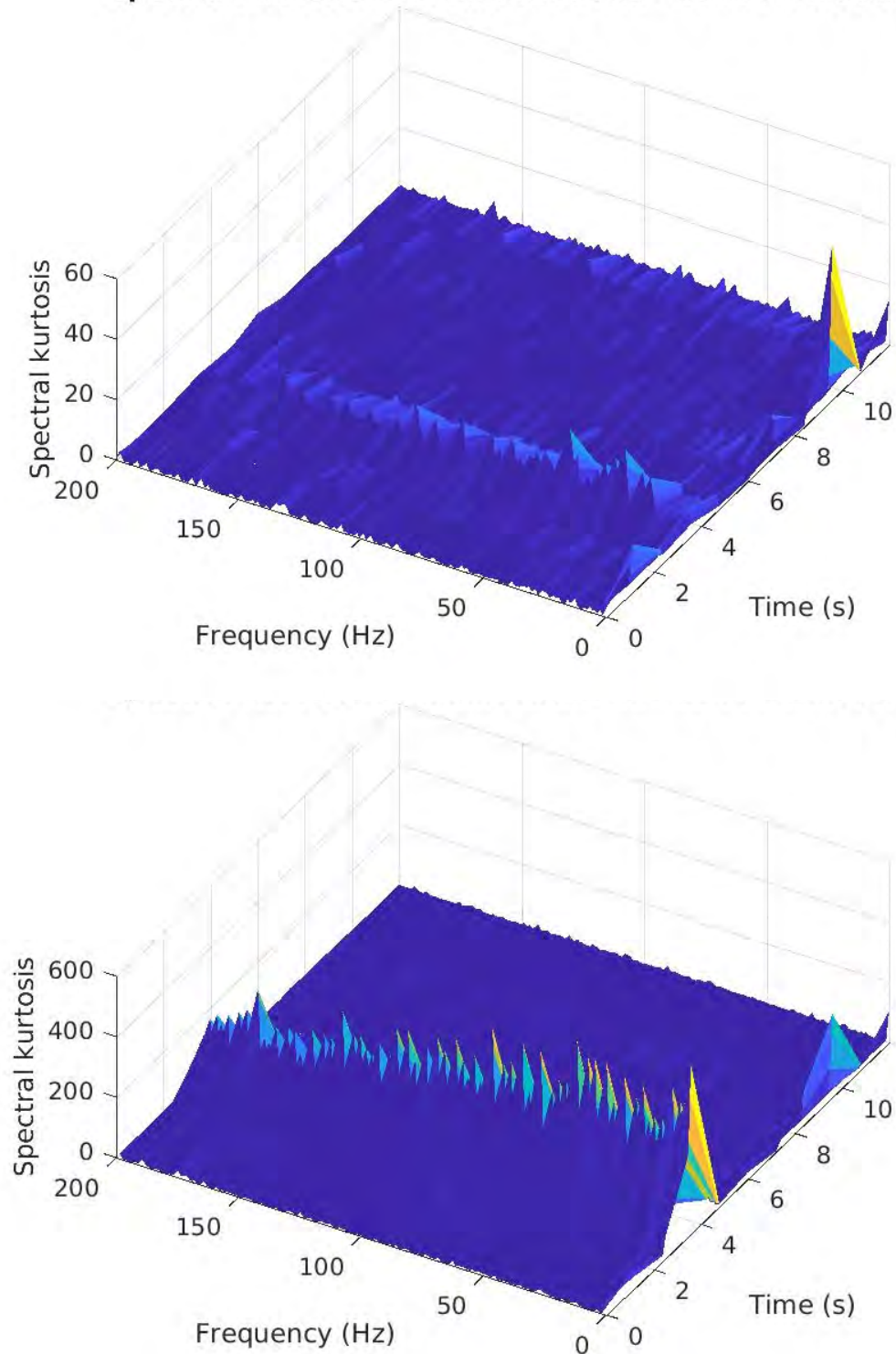


Figure 6.39: Spectral Kurtosis of signal recorded from gearbox of M3 wind turbine with the acoustic sensor with 1ms RMS and 1 s FFT. Top: Input shaft, bottom: planetary region

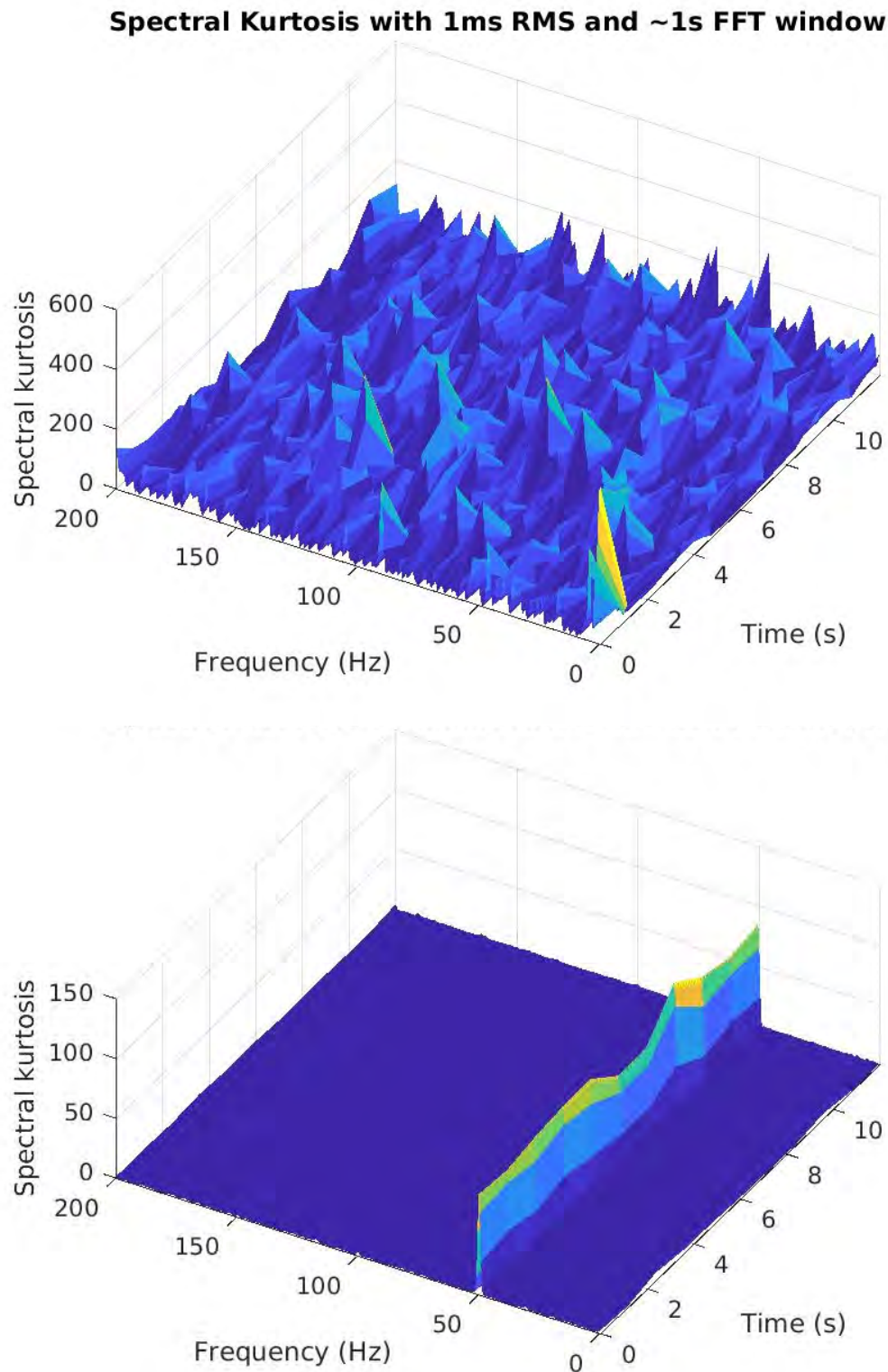


Figure 6.40: Spectral Kurtosis of signal recorded from gearbox of M3 wind turbine with the acoustic sensor with 1ms RMS and 1 s FFT. Top: interim shaft, bottom: high speed shaft region

Although the used techniques were showing the fault in the gearbox and localizing it to the slow speed region of the gearbox, they are not conclusive about the type of fault. The demodulated FFT is also not very conclusive and there is no obvious indication about the fault. Nonetheless, there are several frequencies available in the FFT calculation but the amplitude of the frequencies are not very significant. Figure 6.41 and Figure 6.42 show the calculated FFT for the low speed and high-speed regions of the gearbox respectively.

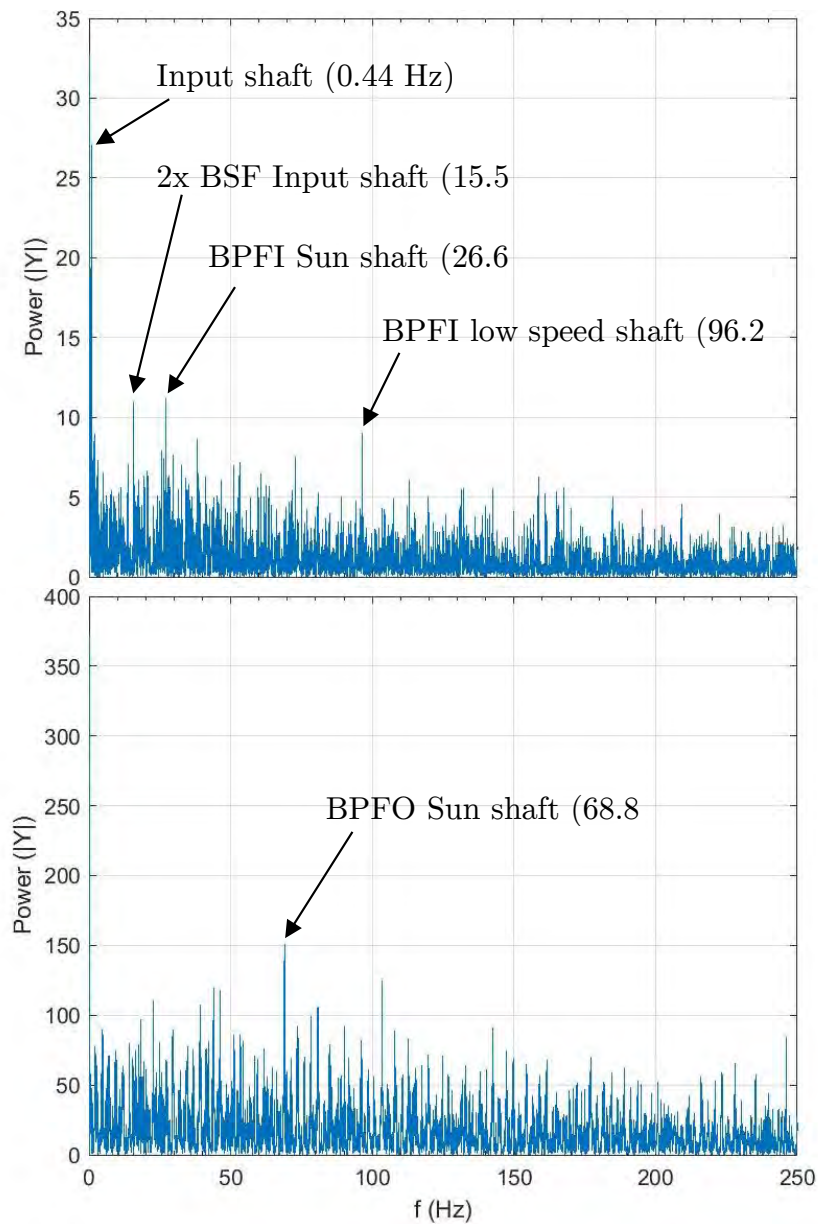


Figure 6.41: The calculated FFT of the demodulated acoustic emission signal recorded from gearbox of M3 wind turbine. Top: input shaft, bottom: planetary region

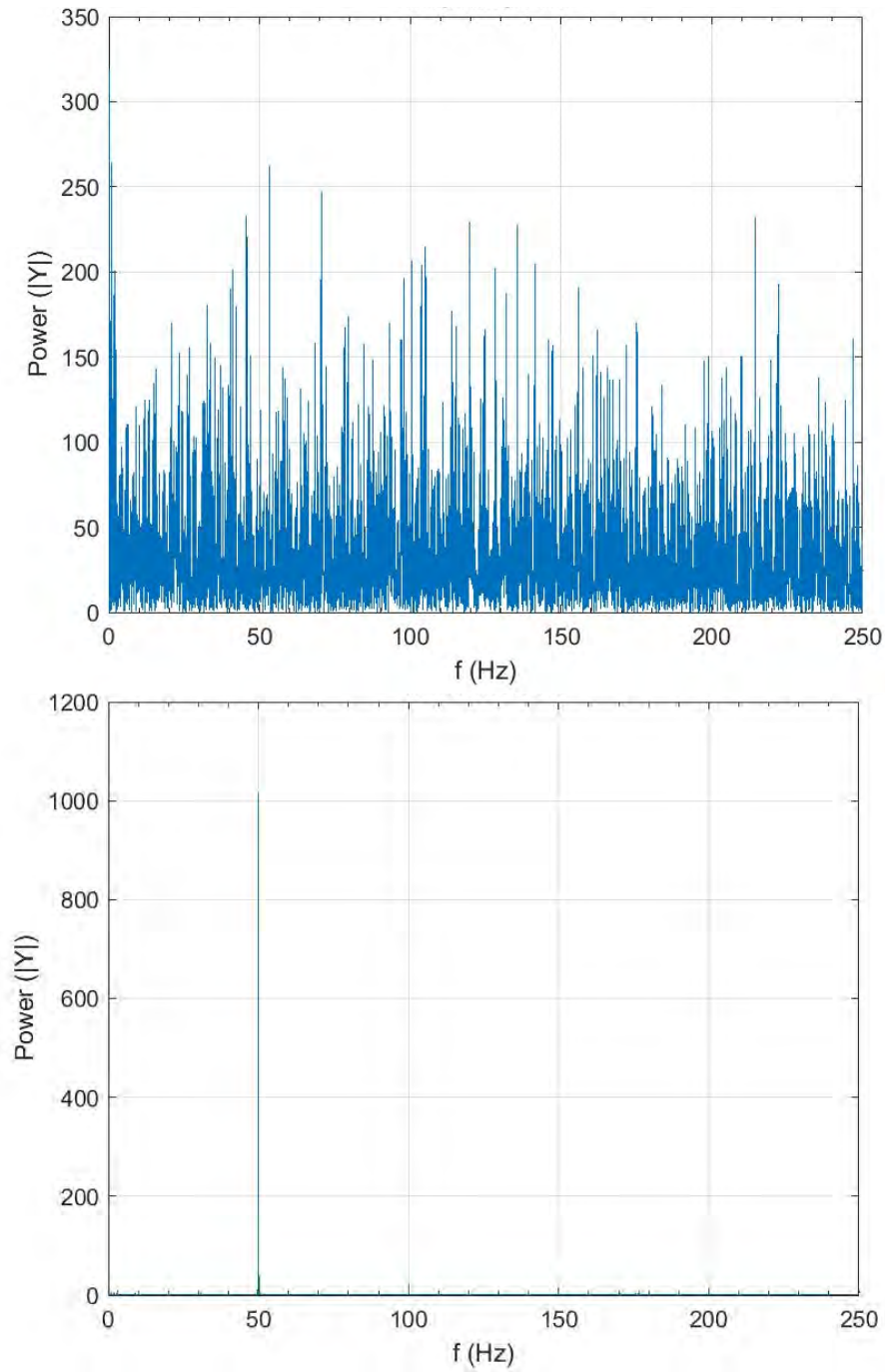


Figure 6.42: The calculated FFT of the demodulated acoustic emission signal recorded from gearbox of M3 wind turbine. Top: interim shaft, bottom: high-speed shaft region

The acoustic signal was further investigation using Kurtogram technique to estimate the optimum demodulation bandwidth and centre frequency as shown in Figure 6.43. The signal was then filtered and demodulated using obtained bandwidth and centre frequency. The demodulated spectrum is presented in Figure 6.44.

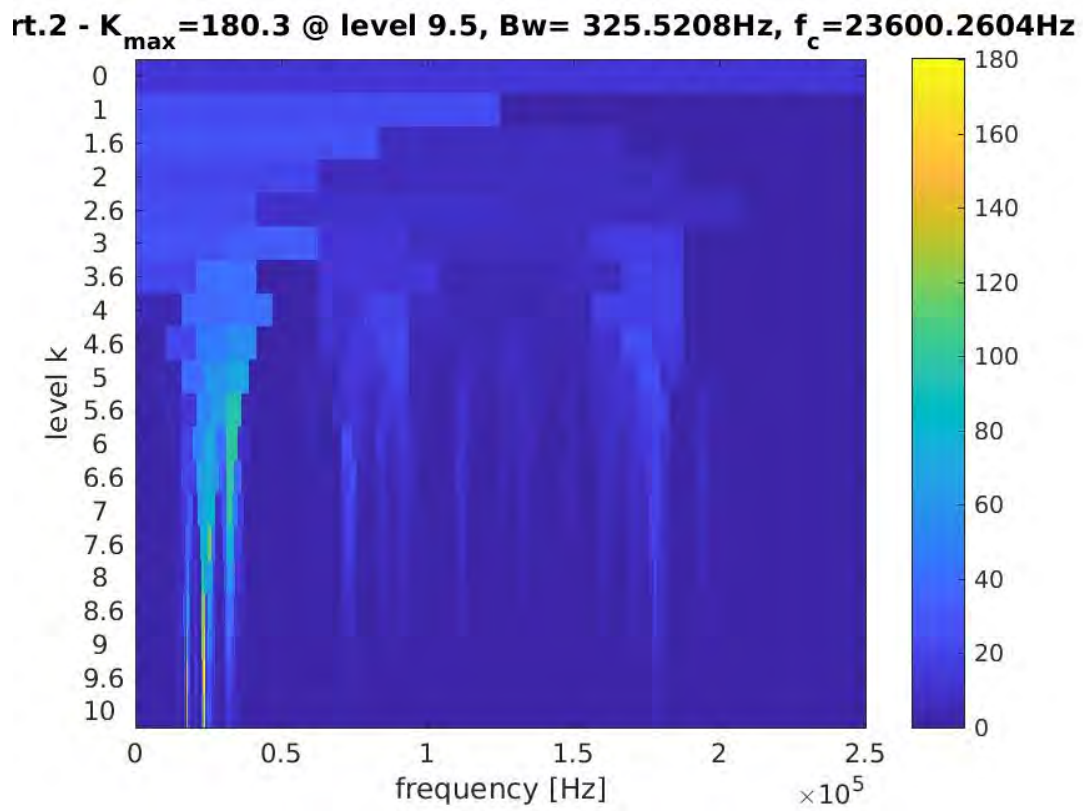


Figure 6.43: Kurtogram performed on the acoustic emission signal recorded from gearbox of M3 wind turbine, showing maximum kurtosis of 180.3 at level 9.5 corresponding to centre frequency of 23.6 kHz and a bandwidth of 325.5 Hz

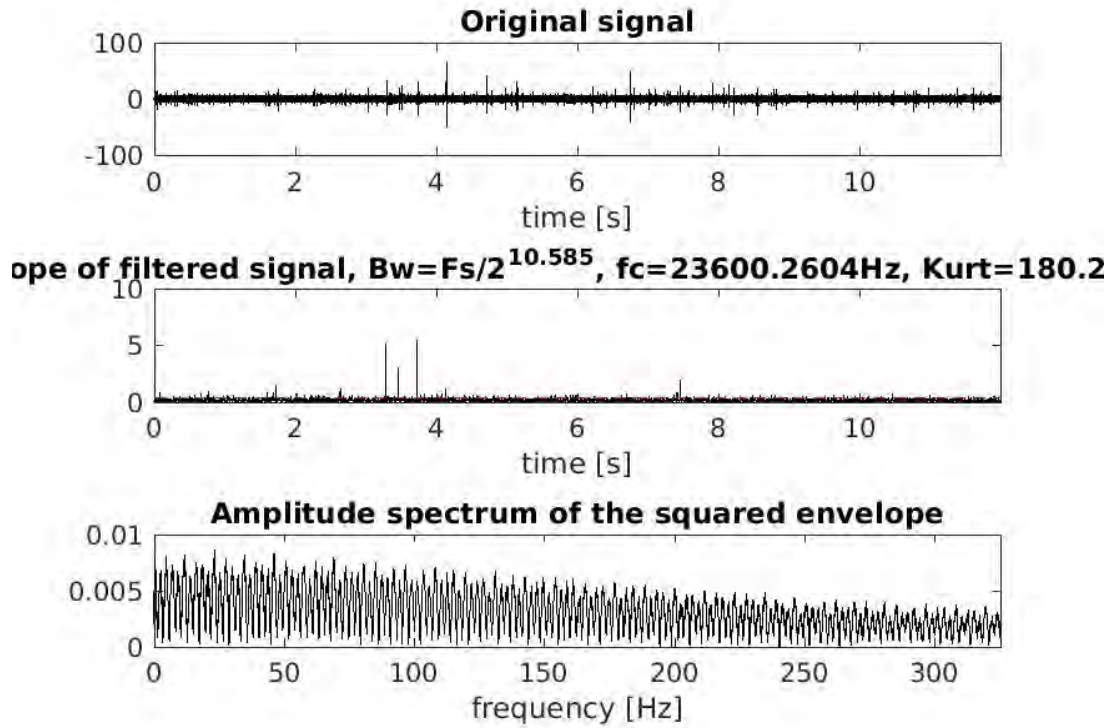


Figure 6.44: Demodulated acoustic signal using Kurtogram showing vibration at 2.37Hz. Top: original signal, middle: signal envelope, bottom: signal spectrum.

As it can be seen, the demodulated signal spectrum is showing 2.37 Hz vibration that corresponds to the planetary defect frequency. To confirm this result, the cyclo-stationary technique was performed on all four channels. The result for low speed and high-speed region of the gearbox is presented in Figure 6.45 and Figure 6.46 respectively.

The cyclic spectral coherence of the low speed region of the gearbox show a very definite result about cyclic frequency at 2.37 Hz and it confirms the previous findings while there is nothing visible at the high-speed region. At this stage, further investigation such as endoscope camera is highly recommended to investigate the extent of the damage on its early stages.

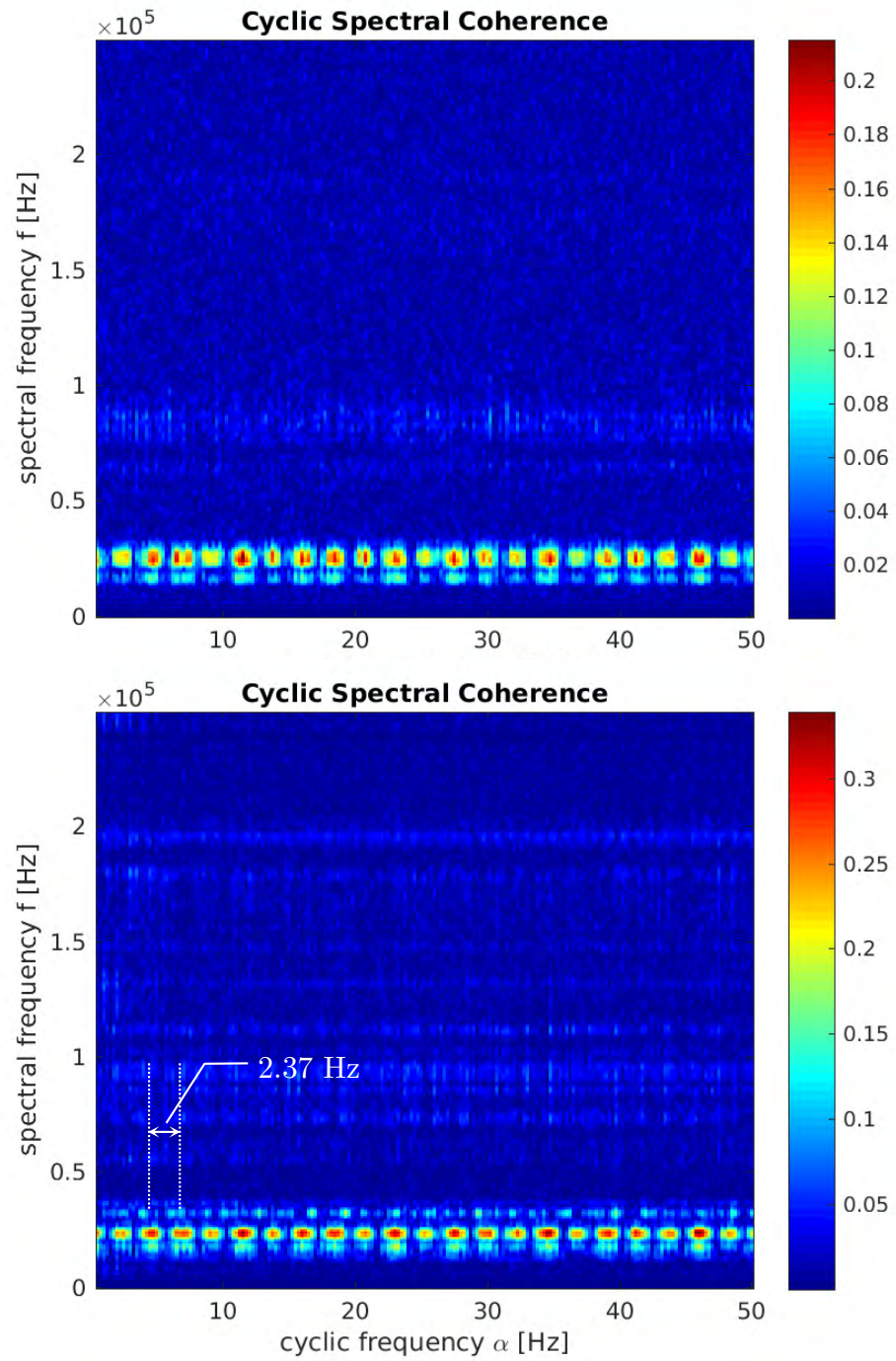


Figure 6.45: The cyclic spectral coherence calculated on acoustic emission signal recorded from gearbox of M3 wind turbine showing 2.37 Hz planetary gear defect frequency. Top: input shaft, bottom: planetary region

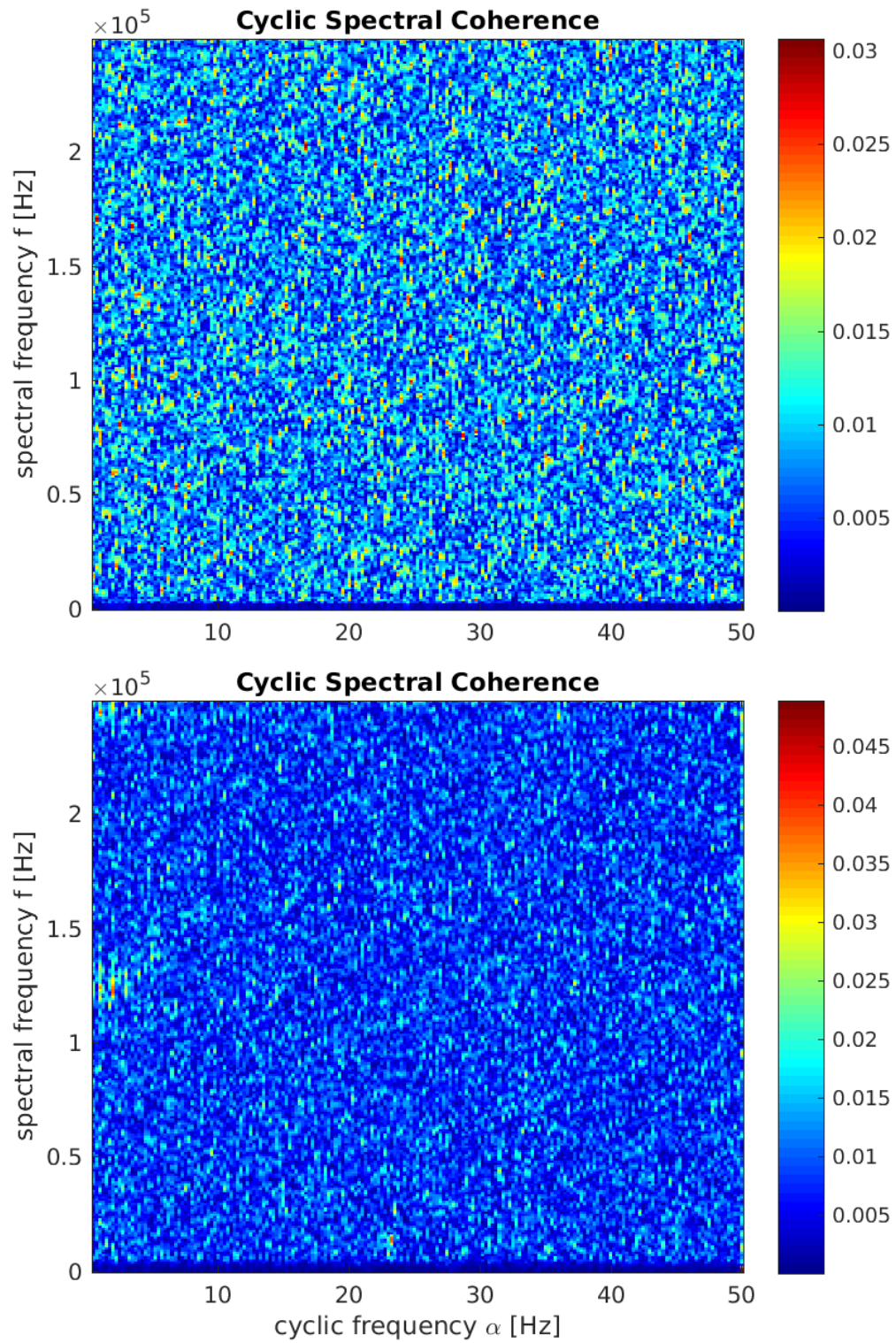


Figure 6.46: The cyclic spectral coherence calculated acoustic emission signal recorded from gearbox of M3 wind turbine. Top: interim shaft, bottom: high-speed shaft region

6.5 Summary

In this chapter, three industrial scale wind turbines were instrumented and studied using vibration and acoustic signals. Various degradation and faults were identified using different signal processing techniques and trend analysis of the collected data.

One challenge to monitor the wind turbines in a farm using vibration and acoustic signals is the amount of data recorded. The recorded data from a wind farm will be extremely large and makes it very challenging to perform signal processing for every turbine in the wind farm.

In the next chapter, the possibilities of signal processing and fault detection using computerised and automation software and alternative solutions such as SCADA systems are explored.

“Research is creating new knowledge”
— Neil Armstrong

Chapter 7

Automated and advanced fault detection

7.1 Introduction

In the previous chapters condition monitoring of wind and tidal turbines using vibration and acoustic signals were investigated. However, the amount of the data required to be processed is extremely large and requires significant time. On the other hand, recording vibration and acoustic signals from the wind or tidal turbines are usually involved instrumentation and introduces more complexity into the system as the sensors itself require maintenance and inspections.

One solution to overcome the signal processing complexity, is to computerise and automate the fault detection. Similarly, using the existing SCADA system in the turbine can eliminate the need for instrumentation of the turbine. However, different approaches are required to perform condition monitoring using SCADA data.

This chapter will explore the possibility of automating the signal processing and performing condition monitoring using SCADA system. Finally, it will propose a novel signal processing chain to detect hidden faults in the gearbox of industrial wind and tidal turbines.

7.2 Customised software developed in MATLAB environment for advanced AE and vibration signal processing

Processing the vibration and acoustic signals recorded from wind turbines is a very time consuming and complicated. A typical 3-stage wind turbine gearbox has more than 50 frequencies corresponding to the gears and bearings. Considering the variable speed of wind turbine and signals recorded from multiple sensors across the gearbox, it is very challenging to accurately identify damage in a subcomponent and verify its severity.

A customised automated signal processing suite has been developed to model, detect and quantitatively evaluate any existing and subsequently evolving faults in a wind turbine gearbox. The main window of the software is shown in Figure 7.1. The developed software allows the user to model and calculate fault frequencies of three types of systems:

- Simple bearing systems: consisting of a single rotating shaft with one or more bearings;
- Simple gear systems: consisting of one or more simple gear stages either parallel, planetary or a mix of both;
- Complex gearbox: consisting of combination of both bearing and gear stages with multiple stages of planetary and parallel gear meshing.

The user will be able to add new bearing models to the software and consequently use it in the modelling and frequency calculations. Both ball and roller bearings are supported by the software, including tapered roller bearings and multi-row bearings. The software is capable of calculating all relevant frequencies such as Ball-Pass Frequency of Outer-race (BPFO), Ball-Pass Frequency of Inner-race (BPFI), Ball Spin Frequency (BSF) and Fundamental Train Frequency (FTF) at the correct speed based on the position of the

bearing in the system. This includes the bearings located at the planets with both inner and outer ring rotating simultaneously.



Figure 7.1: The main window of the developed signal processing software

Any added bearing will be stored in the software database. The user can subsequently modify or remove them using the editing menu as shown in Figure 7.2. It is also possible to export the bearing database or generate a frequency spreadsheet if required.

In the gear design section, the user is able to create a complex gear meshing system consisting of parallel and planetary gears up to a total of 5 stages with any planetary stage having up to 5 planets. After finishing the configuration, the system will generate and visualise the designed system in both 2D and 3D drawings and user is able to export the model to the other CAD or modelling applications for further analysis such as finite element and force analysis. The designed model will be used to calculate the frequencies such as gear mesh and shafts rotating speeds in the system for analysis. A sample 3-stage

planetary gear design is shown in Figure 7.3.

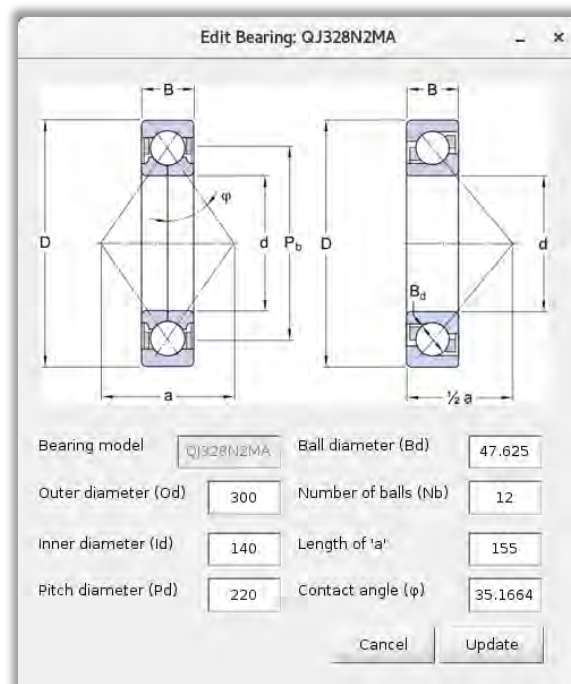


Figure 7.2: Editing the existing bearings in the software bearing database

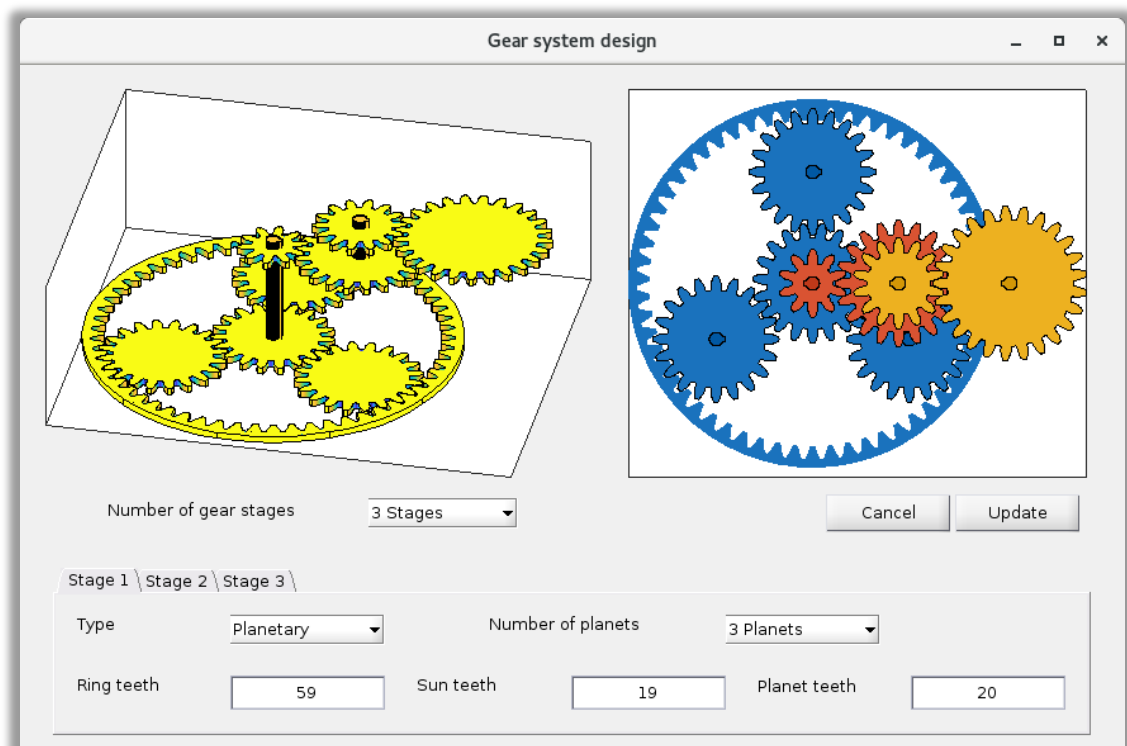


Figure 7.3: Designing a multi stage gear system using the software

After saving the gear configuration, if needed, the user is able to add the bearings in the specific locations using the bearing configuration window. The system will visualise the designed gear system in a simplified 2D side view. The user is able to select the bearing model and click at the desired location in the gear drawings to add the bearing required. Once the user saves the bearing configurations, all relevant frequencies will be calculated automatically and become available for diagnosis and further evaluation as required. This configuration window is shown in Figure 7.4.



Figure 7.4: Bearing configuration window allowing the user to add bearings to the system interactively

The user is able to load various types of acoustic emission and vibration data files such as:

- National Instruments Data Acquisition (DAQ);
- Common Data Format (CDF);

- National Instruments Technical Data Management Solution (TDMS);
- MATLAB Formatted Data (MAT);
- Spreadsheets tables (XLS/XLSX);
- ASCII/Text tables (TXT, CSV, TSV);

The loaded file will be scanned and parsed automatically for any information captured such as sampling rate, number of channels used, date, time or user comments as shown in Figure 7.5. It is also possible to load multiple datasets into the system and switch between them. This is shown in Figure 7.6. The user is also able to save the current state of the software including the loaded datasets and any configurations into a single file and load it back into software at later time.



Figure 7.5: After loading a data file, basic information from the loaded data is shown to the user

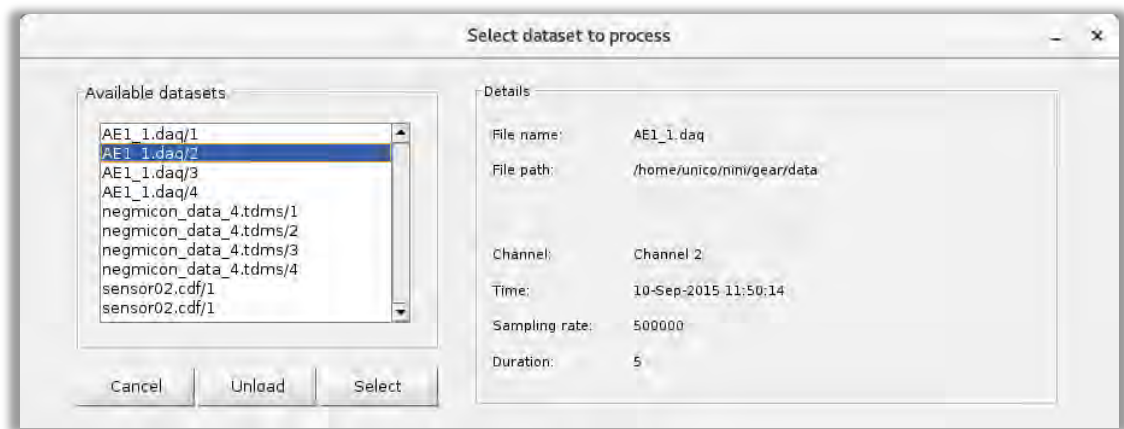


Figure 7.6: Selecting a dataset or data channel to process from several loaded datasets.

Various algorithms are available to the user for signal analysis via the tools menu. This menu and its items are shown in Figure 7.6. It is possible to apply multiple algorithms sequentially as well as user defined algorithms. The user defined algorithms have to be written in MATLAB and then wrapped in a function with data and other information such as sampling rate in and out. The user defined script editor is shown in Figure 7.8.



Figure 7.7: The tools menu showing various signal processing techniques available to the user.

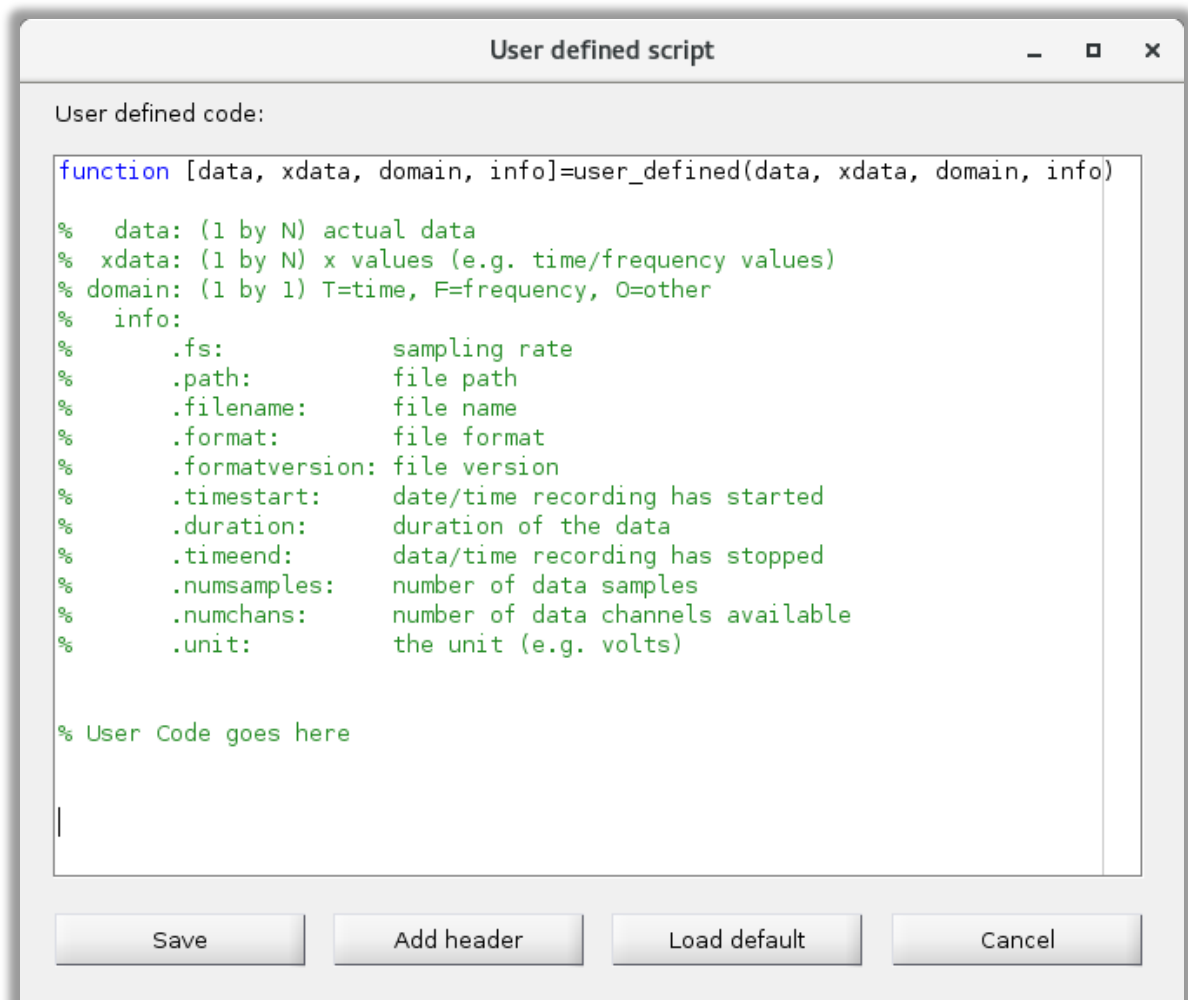


Figure 7.8: User defined MATLAB scripts can be added by the user using syntax coloured editor window and be used in batch processing or applied to the loaded data file.

One important feature of the developed software is batch processing which allows the user to process large data files automatically. The user is able to set a chain of processes and configure each process along the chain (e.g. the type of FFT windowing and its resolution as shown in Figure 7.10) and apply it on data files. Then, the system tries to obtain the rotational speed for each file from the available information or guess the speed from the frequency peaks and subsequently extract or mark or carry out trend analysis of the characteristics frequencies of the designed system on the data files. The results can be saved as figures or MATLAB files or both depending on the user's preferences. This batch processing configuration window is shown in Figure 7.9.

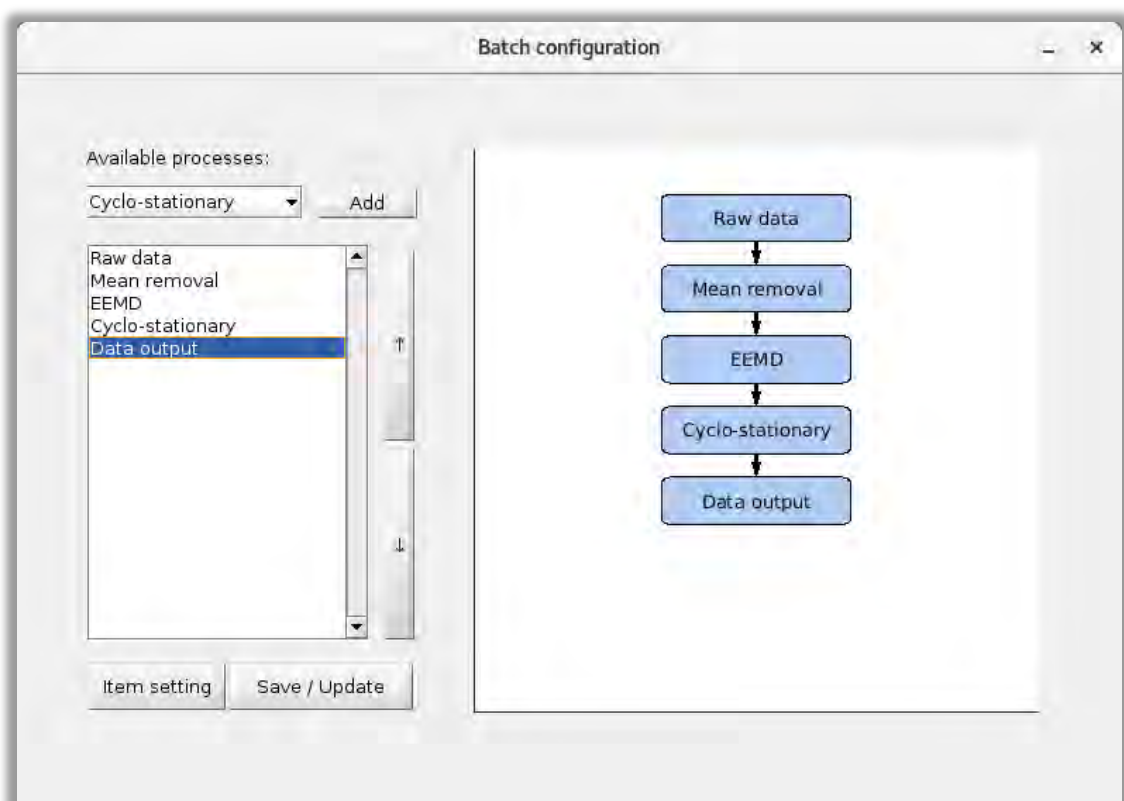


Figure 7.9: The batch processing configuration window allows the user to create a chain of processes and apply it on any number of data files. Each item can be configured by user separately.

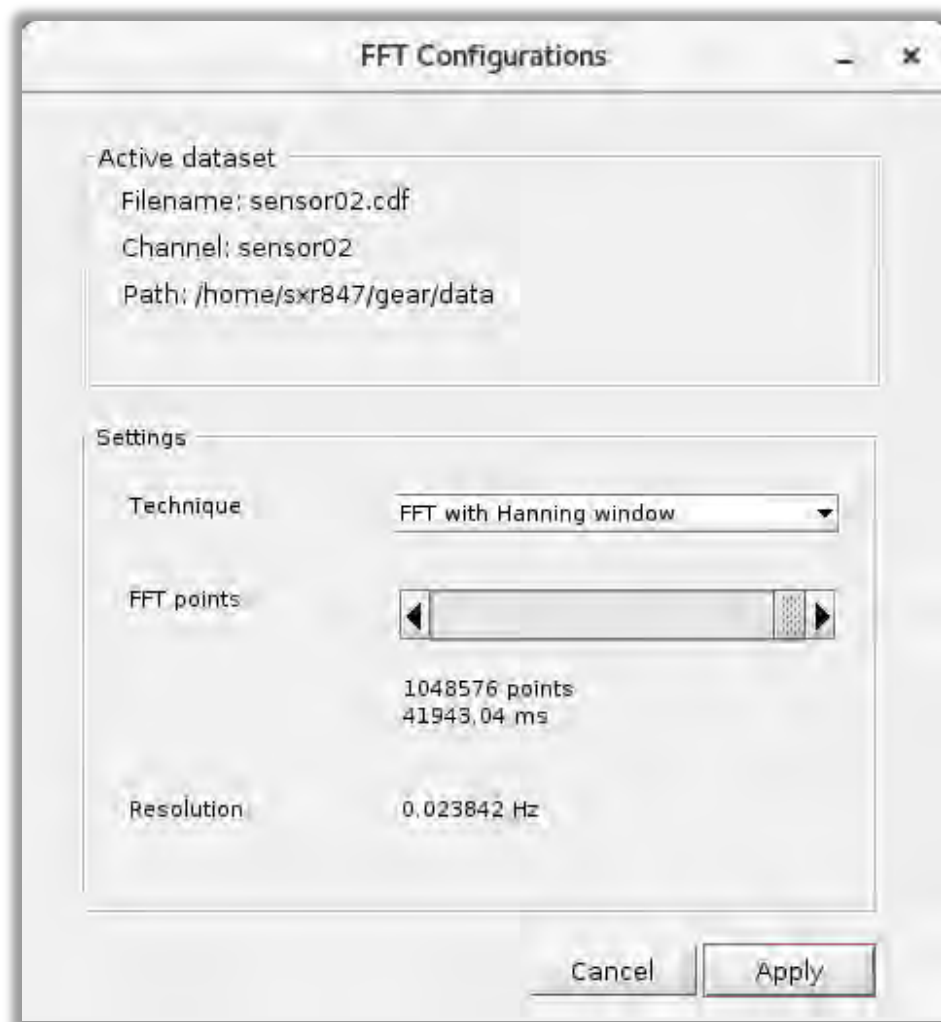


Figure 7.10: An example of signal processing configuration window showing the Fast Fourier Transform configurations available to the user.

Several interactive signal visualisation tools are available to user to view and investigate the signals for fine tuning of the signal processing parameters. In particular the circular time plot (Figure 7.11) helps the used to view and investigate any irregular periodic characteristics in the signal. Similarly, the frequency explorer provides the ability of viewing the frequency spectrum and place markers at characteristics frequencies of the system and fine-tune the speed and tolerance of the system. This is shown in Figure 7.12.

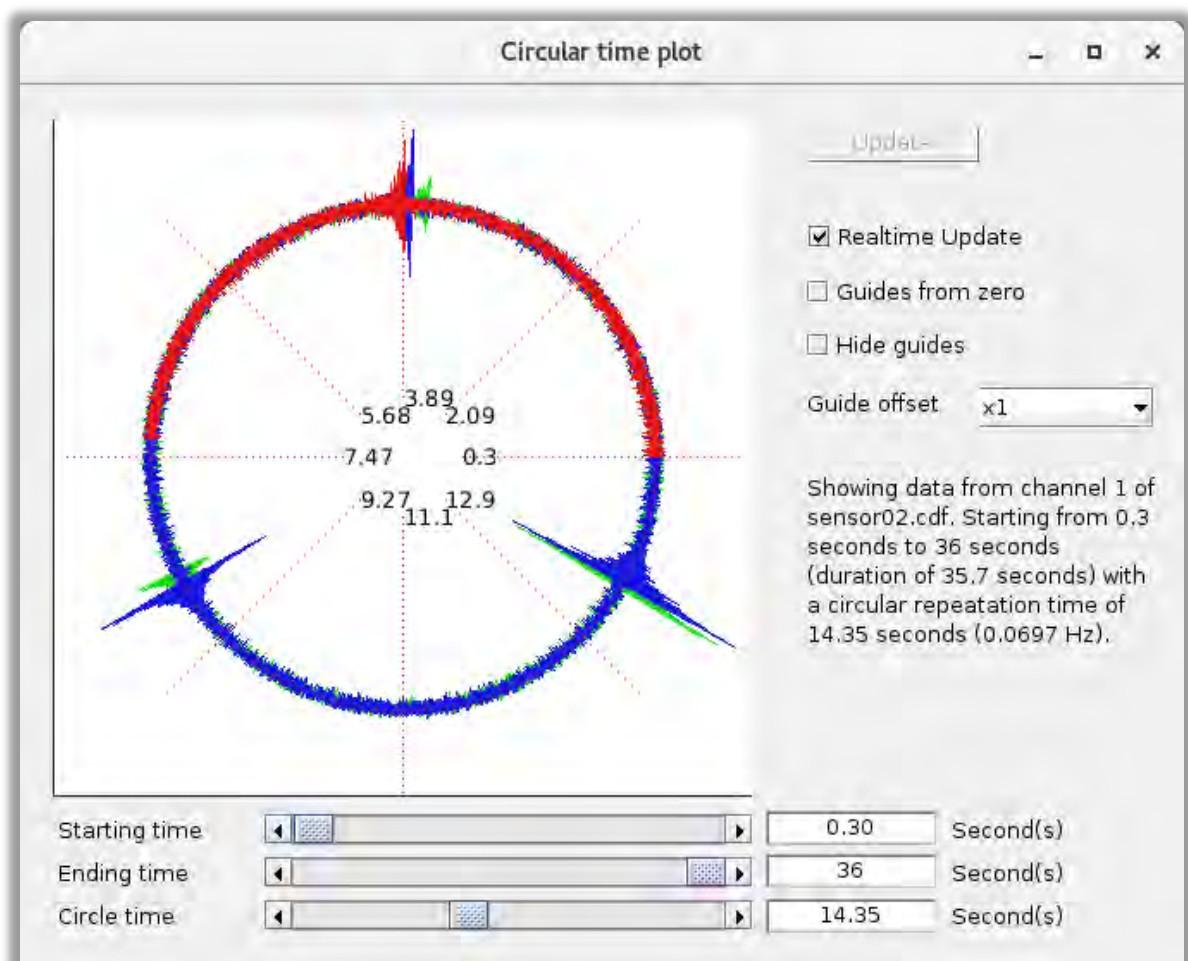


Figure 7.11: Circular plot allows the user to visualize the signal in a unique way to look for any quasi cyclic or partially periodic features.

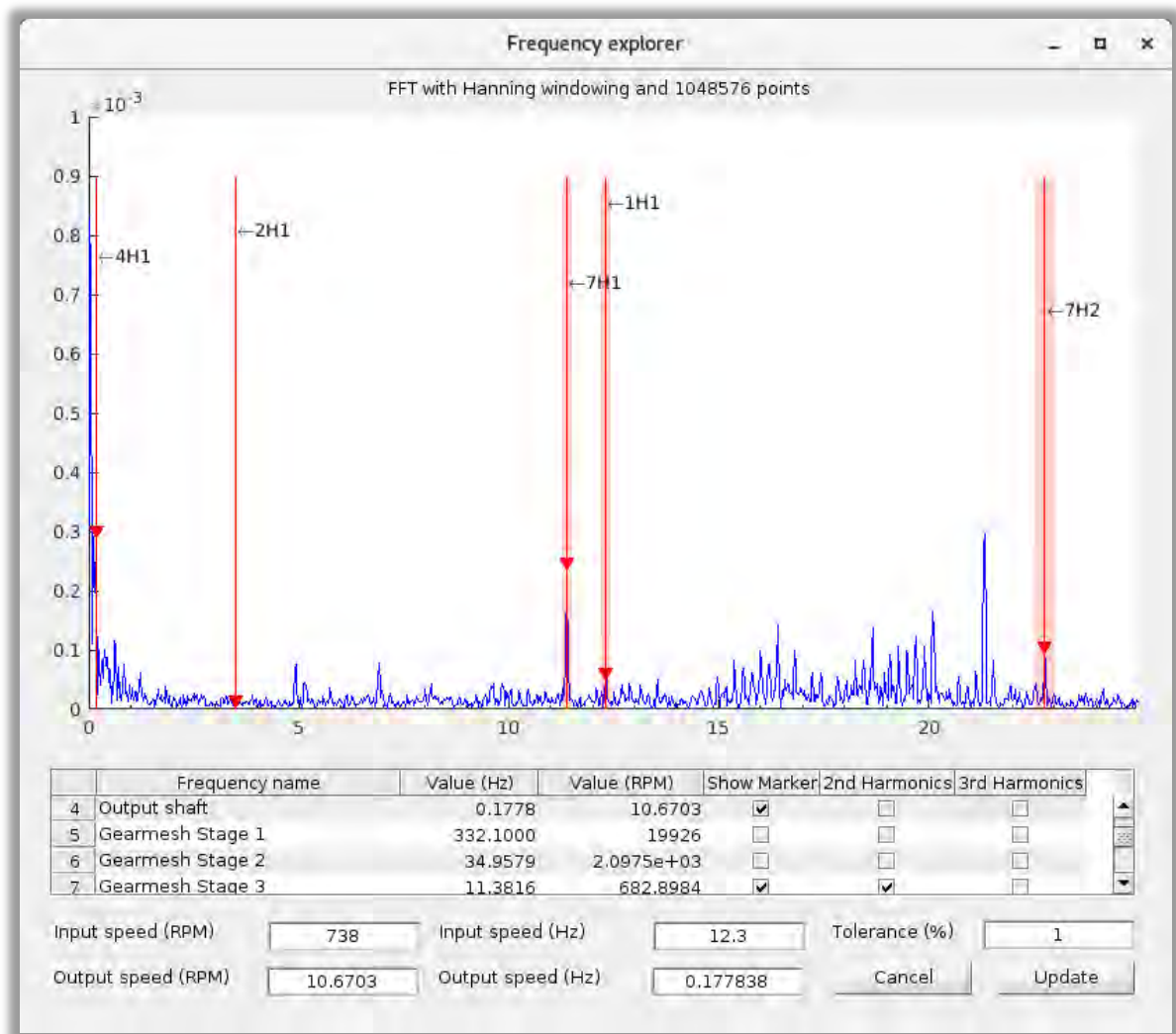


Figure 7.12: The frequency explorer allows the user to view and mark the system characteristics frequencies on the loaded data file

7.3 Machine learning

One of the most advanced techniques for analysing large datasets is machine learning. Unlike classical computer programming with explicit rules and conditions to follow, machine learning is trying to perform a task by establishing and learning the relation between input and output implicitly by the machine itself.

This technique can be further divided into two category of supervised and unsupervised learning. The supervised learning branch mainly relies on the user to train the system using known examples. This is normally done using a labelled dataset known as training

dataset. The training dataset consists of corresponding inputs and expected outputs to the system. The accuracy and the performance of the trained system will depend on the size of the training dataset. The bigger and more versatile the training dataset is, the better the system will be trained.

In the unsupervised learning approach, the training dataset is not available. Thus, the system tries to find mutual features in the dataset and create groups or clusters based on the presence or absence of those common or shared features. The techniques falling into this category are usually trying to mimic human reasoning and finding hidden features and patterns in the dataset.

Numerous learning algorithms for pattern recognition and data classification are available to use. Depending on the data type and requirements, the most appropriate techniques can be tested on the dataset. To evaluate the performance of machine learning on wind turbine data, based on the technique complexity and computation, three different techniques were considered. These are:

- Decision Tree;
- Support Vector Machine (SVM);
- Artificial Neural Network (ANN);

Each of these techniques will be discussed briefly here.

7.3.1 Decision tree

The Decision Tree technique is one of the most widely used and practical methods for data classification [150]. Decision Tree is a very simple yet powerful tool and very similar to flowchart algorithms in nature. As the name suggests, it has a tree-like structure consisting of nodes and branches. At each node of the tree a feature of the dataset will be tested. Based on the test result the Decision Tree follows the relative branch leading to the next node and progresses towards the end of the branch. Figure 7.13 shows an example of such decision trees for servicing a gearbox using 4 features.

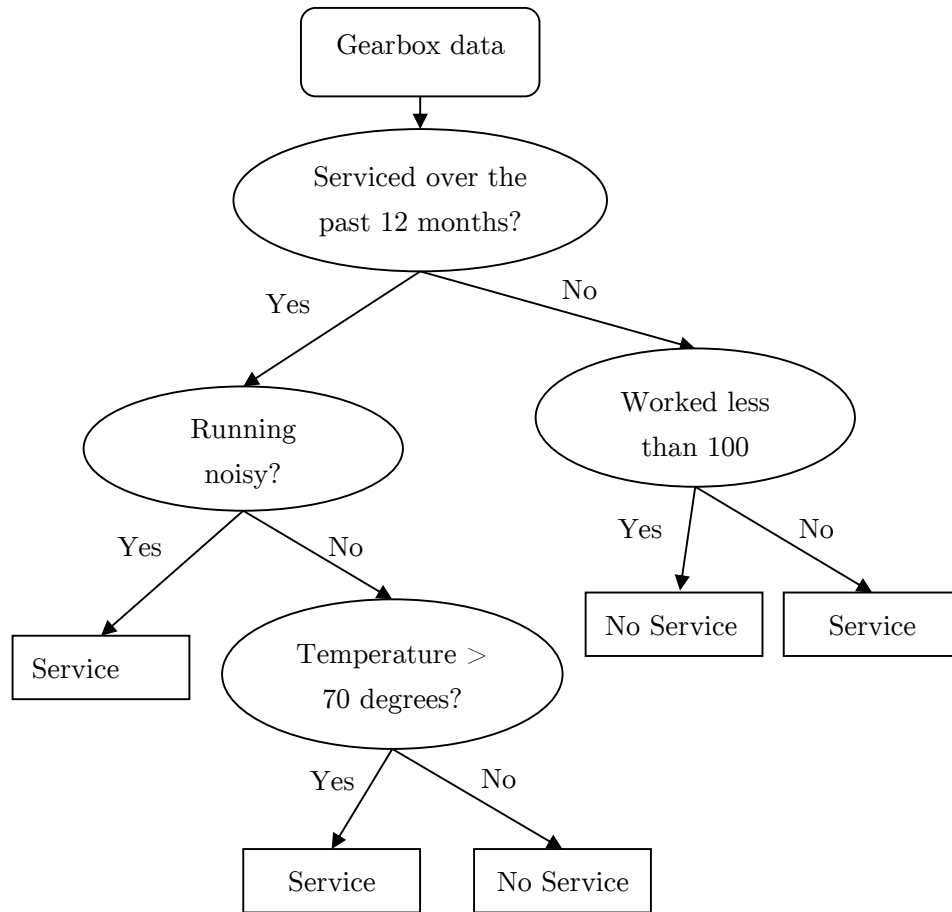


Figure 7.13: A simple decision tree for servicing a gearbox

During the training procedure, or building the decision tree, the branches split the input data into subsets based on the tests on different features of the data. This is done in a way that splits the data into subsets with distinct labels or classes. This process continues iteratively down each branch until the entire subset belongs to a single class or further splitting does not make any significant contribution to the final result.

7.3.2 Support vector machine

Support vector machine or network is a fairly recently developed technique and is commonly used for binary classification [151]. This technique has a very simple structure and does not require many data features for classification. This makes it a very robust

classifier among other classification techniques [151].

In the context of this technique, each data entry is treated as a vector with the features representing the dimensions of that vector. Thus, a data with n features is characterised as an n -dimensional vector in an n -dimensional space. Figure 7.14 illustrates a simple 2-feature dataset classification using support Vector Machine. The aim of Support Vector Machine is to separate the n -dimensional data into $(n-1)$ dimensional hyperplane. While there can be many possibilities to separate the data, the goal of the classifier is to separate the data in such way that the classes are distanced from each other at maximum and the error is at its minimum as illustrated in Figure 7.14. As it can be seen, both red and blue lines have separated the data completely. However, the distance between classes (the corresponding shaded area around each line) is very small if data are separated using the red line, while the blue line provides the maximum distance between the two classes.

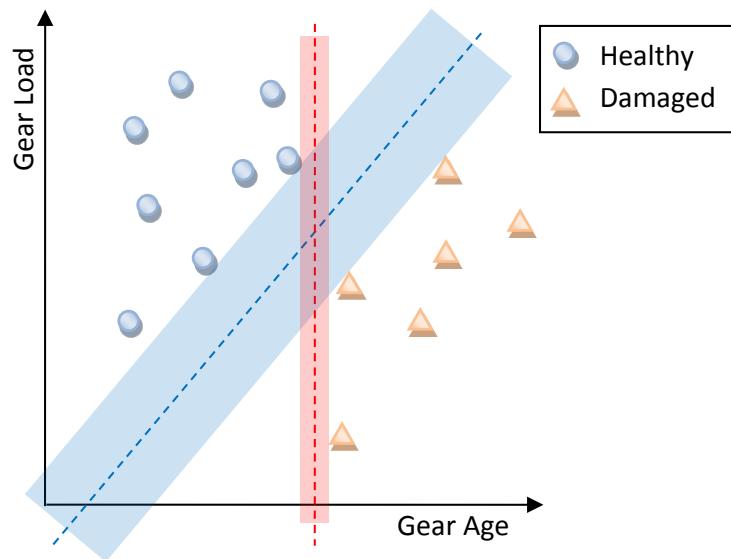


Figure 7.14: An example of SVM classification using a simple 2-dimensional data

During the training progression, two parallel hyperplanes are defined as boundaries and are distanced towards opposite data class such that the maximum distance from each data point is achieved while the hyperplane is not crossing any point from opposite class. This hyperplane is known as the maximum-margin hyperplane [151]. If there are more

than two classes, it is possible to find the optimum hyperplane using a technique known as one-versus-the-rest [151] that select one class versus the rest of classes all combined together at each time.

7.3.3 Artificial neural network

The ANN technique is usually employed when a problem cannot be formulated either as an algorithm, or an analytical solution. The ANN technique is very similar to the human neural system as a concept, trying to mimic biological brain learning. An ANN consists of neurons in the form of simple processing units and weighed connections between those neurons. A typical structure of an ANN is as shown in Figure 7.15.

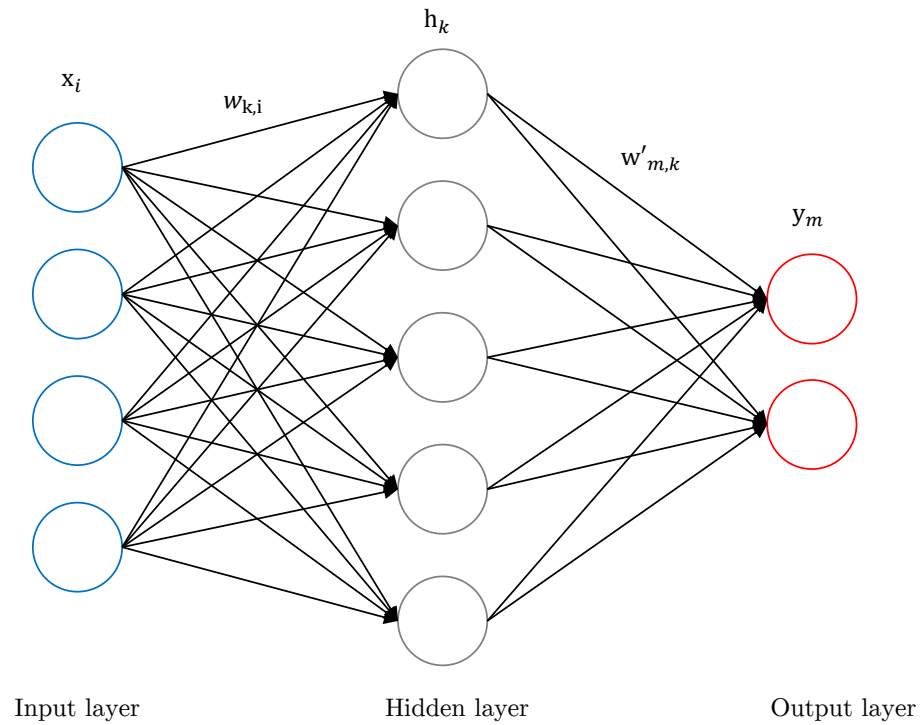


Figure 7.15: Typical structure of an artificial neural network

The ANN can be divided into 3 layers, which are known as input, hidden and output layer. The nodes in the input layer are passive and only duplicate the received value and

propagate it through multiple outputs. The number of nodes in the input layer depends on the number of inputs to the ANN. The hidden layer is containing active nodes that modify the data in function of the weights. A typical active neuron is illustrated in Figure 7.16 and its mathematical representation is provided in equation 7.1.

$$Y_k = \varphi\left(\sum_{j=1}^i w_{k,j} \cdot x_j + b_k\right) \quad (7.1)$$

It is possible to have more than one hidden layer in the network but usually there is no reason to have more than two hidden layers in any ANN [152]. The output, similar to the hidden layer, contains active nodes that produce the output of network. These nodes combine and modify the data in order to generate the output. The number of nodes in this layer depends on the number of outputs or targets required. The strength of the connection between nodes are defined as weight that can be different for each node. For example, in Figure 7.15 the strength of connection between input node x_2 and hidden node h_5 is defined by weighting factor $w_{2,5}$.

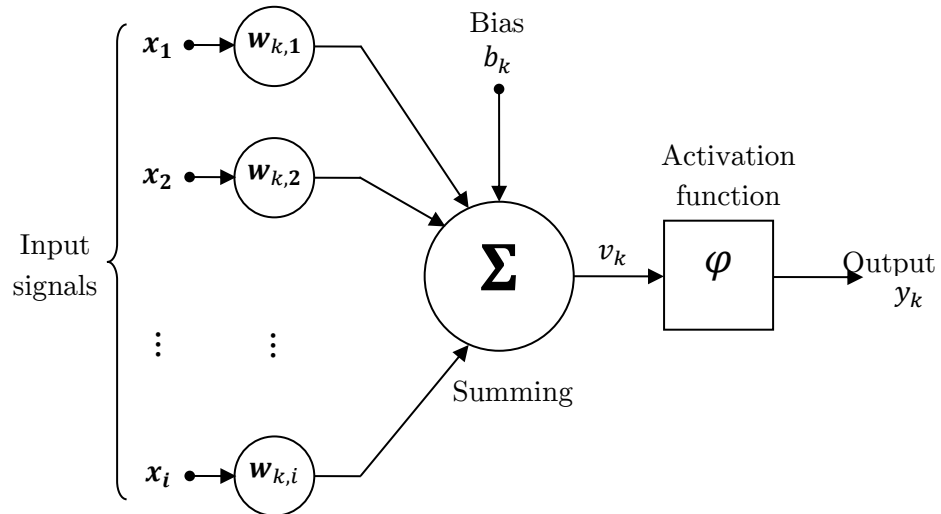


Figure 7.16: A typical active neuron of a neural network [152].

Although the number of input and output nodes can be selected based on the number of input and output to the network, the number of nodes in the hidden layer and the

number of hidden layers required in the network are not easy to define. There are many different techniques and suggestions about how to select the near-optimum number of nodes depending on the number of inputs and outputs or classification tasks. Some of the more advance prediction techniques use genetic algorithms to calculate the number of required nodes [153].

During the training process, a set of data is provided to the ANN for pattern recognition. For example, in wind turbine condition monitoring, the input data will be a selection of conditions or features obtained from the sensors installed on the wind turbine. The expected output of the network will be the condition of the wind turbine. Using the provided data, the system will fit different weights to the network such that the desired output is generated.

7.3.4 Training, validation and test datasets

Machine learning usually requires a very large training dataset that covers as many situations as possible to train comprehensively and minimise the detection error. However, in many cases, this is not easily achievable and the amount of data available for training is limited.

To overcome this problem, it is possible to use a technique known as k-fold cross validation [154]. In this technique, the dataset is randomised and a part of data is kept away for testing the system. This is known as test dataset. Then the remaining data is divided into k equal or nearly equal groups or folds.

Each time, one fold is kept as validation dataset and the remaining k-1 folds are used to train the system as training dataset. The trained system is tested each time using the validation dataset in that fold to evaluate the system performance. Finally, the system performance is tested using the test dataset that was separated from the original dataset. This is illustrated in Figure 7.17.

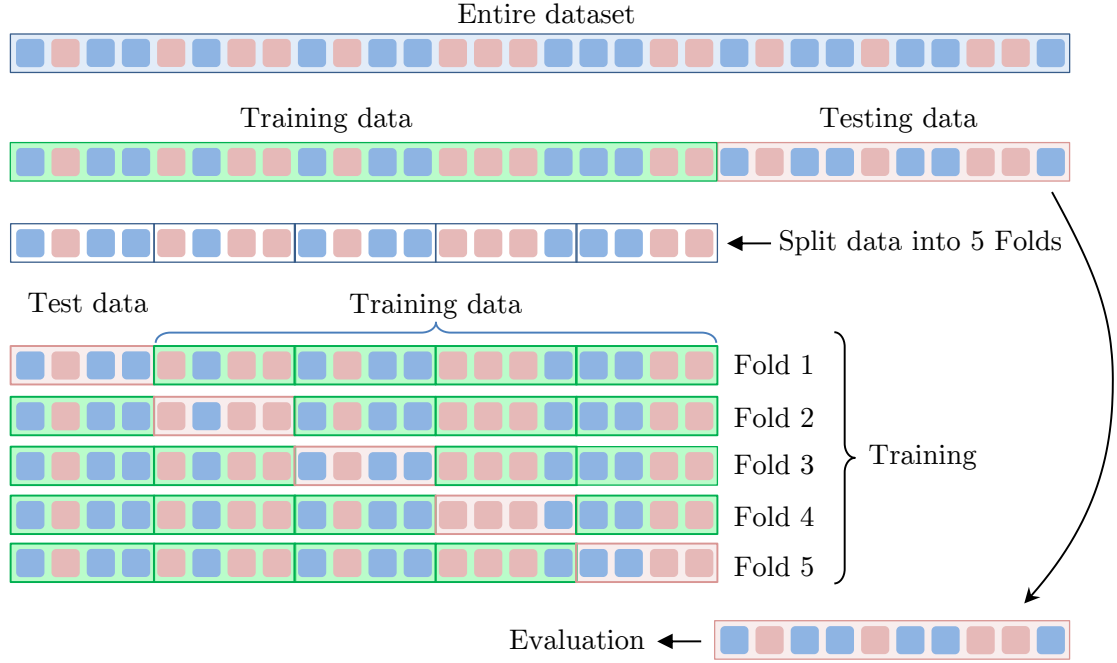


Figure 7.17: k-fold cross validation technique with k=5

7.3.5 Classification results

As it was mentioned earlier in Chapter 6 a month worth of vibration signal will produce more than 15,000 data files and hundreds of gigabytes of data that is very large and extremely difficult to handle and analyse. One solution to overcome this problem is to use the SCADA sensors readily available on the wind turbine. However, the drawback of using SCADA data is the limited sensor types and their sampling rates. The SCADA on-board sensors are typically sampled every 10 minutes, which is extremely low for typical signal analysis, and fault detection.

Nevertheless, these data can be used for gradual and long-term trend analysis. However, it is possible to use machine learning and advanced classification techniques to classify the results and identify certain developing faults. Table 7.1 lists the available SCADA sensors in a MW wind turbine.

To evaluate the performance of the machine learning, the SCADA data from 3 1.5MW

Table 7.1: Typical SCADA sensors in a MW wind turbine

Sensor	Unit
General Accumulator Blade 1	bar
Autopilot Status	—
Yaw motors CCW turn contactors Acknowledgement	Counter Clock wise
Yaw motors CW turn contactors Acknowledgement	Clock wise
Active energy counter	Kw
Power factor	—
Status	—
Turbulence level	—
Oscillation level	—
Vibration level	—
Pitch 1/2/3	—
Power	degrees
General Accumulator Pressure	Kw
Brake Pressure	bar
Hydraulic group pressure	bar
Power factor set point	bar
Pitch set point	bar
Hydraulic group oil temperature	degrees
Power factor set point	°C
Gearbox oil temperature	°C
Environmental temperature	°C
Drive end side generator bearing	°C
Non-drive end side generator bearing	°C
Number 1 generator winding temperature	°C
Nacelle Temperature	°C
Lower radiator temperature	°C
Upper radiator temperature	°C
Number 1 gearbox bearing temperature	°C
Transformer 1/2/3 temperature	°C
Grid voltage	V
Total reactive power	Kw
Generator speed	Rev/min
Rotor speed	Rev/min
Wind speed	m/s
Yaw	degrees

wind turbines within a single wind farm was used. In January 2013, one of these turbines had a serious failure in its generator rotor windings as shown in Figure 7.18. The generator failure has occurred in 20th of January and the new generator was installed on 22nd of January when the turbine returned to normal operation. Figure 7.19 shows the generator temperature recorded in SCADA data for the failed wind turbine.



Figure 7.18: Generator rotor winding failure

To select the data for training the system, one week prior to the failure was assumed to be faulty and one week after the repair was assumed as healthy data. Same period of data from the other two wind turbines was selected and marked as healthy. This is illustrated in Figure 7.20. A total of 5 relevant sensors from Table 7.1 was selected to generate the feature matrix required for classification and training the system. These sensors were ambient temperature, generator temperature, generator speed, vibration level and generated power. The temperature feature was calculated by subtracting the ambient temperature from the generator temperature. Some of these features are plotted in Figure 7.21. The generated feature matrix to train the system is presented in Table 7.2.

Using the generated feature matrix and the three classification techniques described earlier, the data was classified and the trained system was evaluated. The detection result

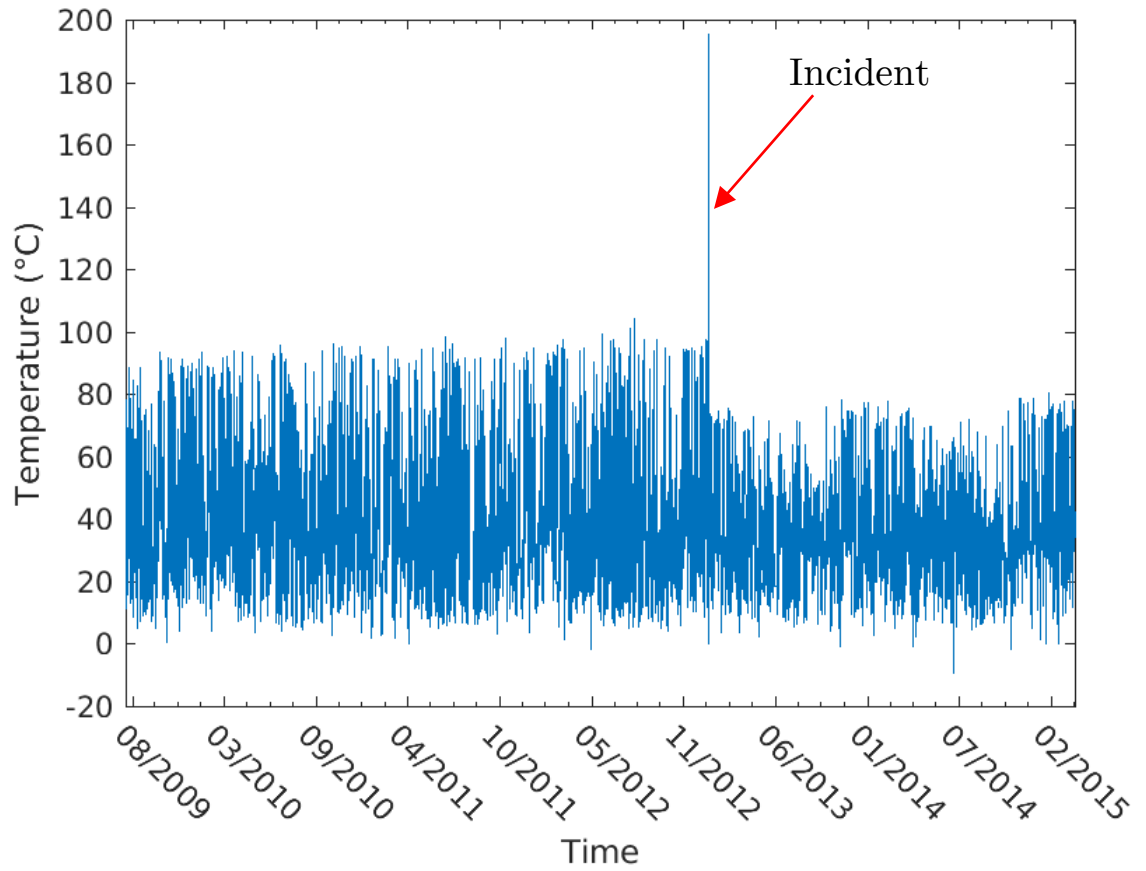


Figure 7.19: Generator temperature over time for the failed generator

Table 7.2: Feature matrix generated for training the system.

Sample	Temp	Speed	Vibration	Power	Label
1	10.50	769.13	0.20	113.12	Healthy
2	12.66	769.16	0.19	64.01	Healthy
3	14.82	769.19	0.15	86.18	Healthy
4	16.97	769.22	0.20	73.55	Healthy
5	23.02	769.40	0.16	90.86	Healthy
6	23.83	769.43	0.21	97.60	Healthy
...	...	...	...	...	...
1447	09.77	769.23	0.19	86.11	Faulty
1448	11.86	767.98	0.16	34.31	Faulty
1449	13.96	766.73	0.19	75.10	Faulty
1450	16.07	765.48	0.19	63.76	Faulty

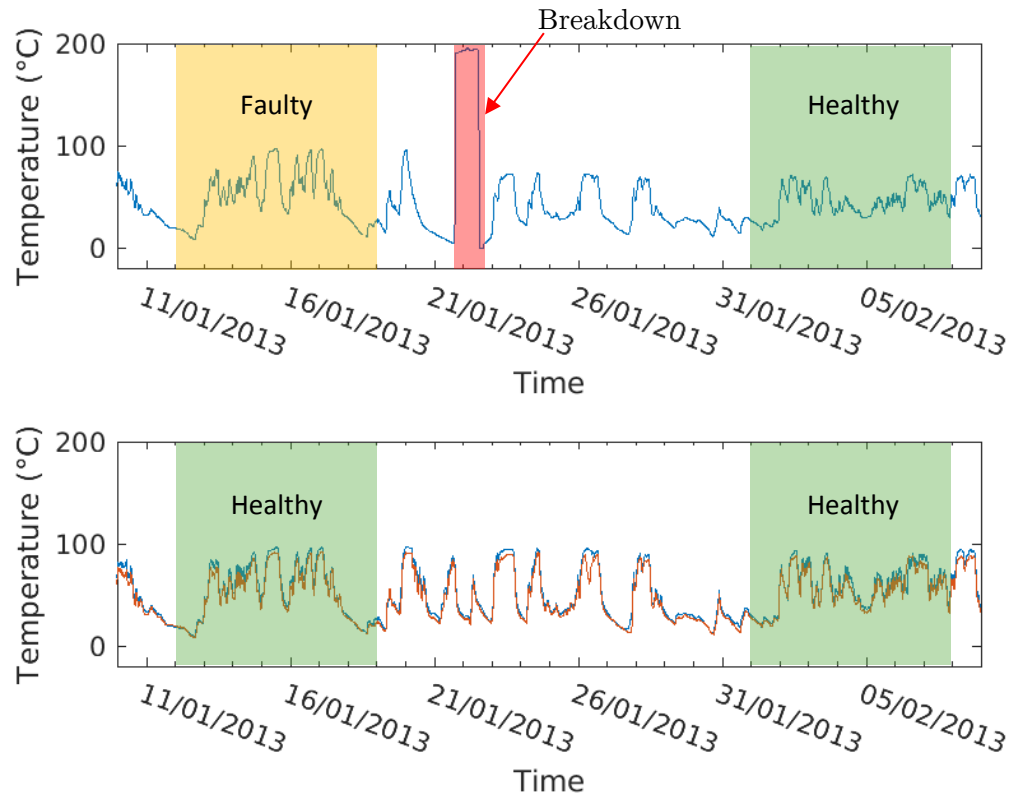


Figure 7.20: Generator temperature of the three wind turbines over time; top: faulty wind turbine, bottom: two healthy wind turbines.

is presented in Table 7.3 As it can be seen all three classifiers are performing reasonably well in detection the fault. In particular, the artificial neural network overall performance was the best within the three classifiers, although the difference is insignificant.

Table 7.3: Comparison of the detection performance of the three different classifier

		Detection (%)		
		Faulty	Healthy	Overall
Classifier	Tree	75.9	89.3	84.8
	SVM	72.8	93.6	86.7
	ANN	73.0	93.9	86.9

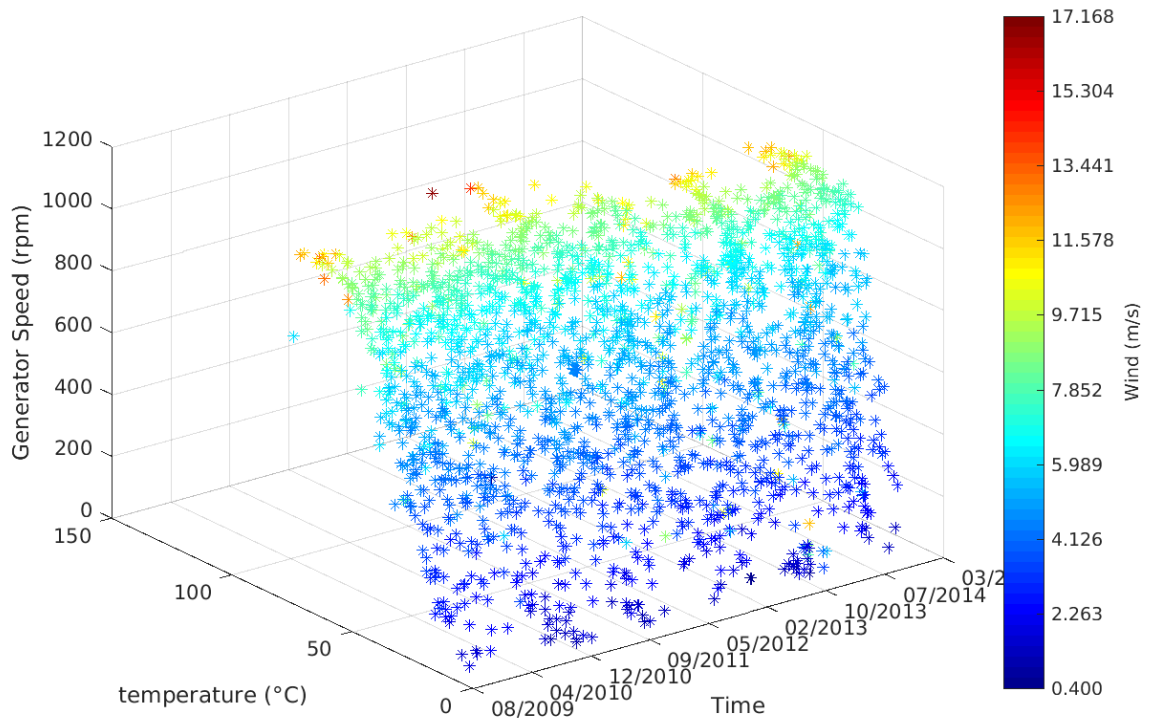


Figure 7.21: Interdependency of temperature, generator speed and wind

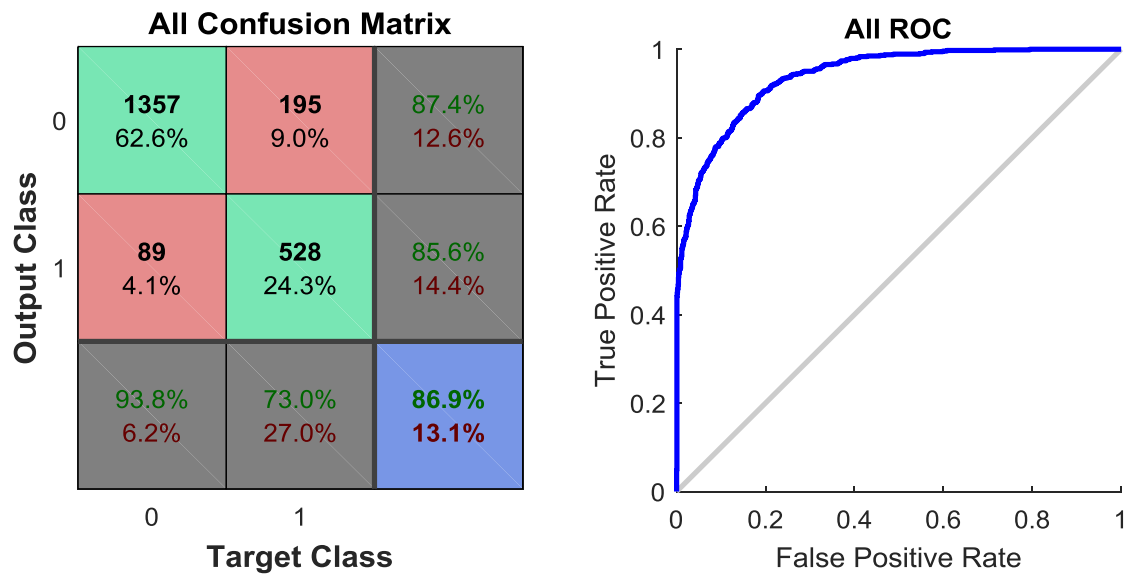


Figure 7.22: The performance of the artificial neural network (ANN) classifier as confusion matrix and receiver operating characteristic (ROC) curve

7.4 Enhanced signal processing

As it was demonstrated earlier, finding the fault frequencies in the gearbox is a very challenging task, requiring extensive experience, and advanced signal-processing techniques. Techniques such as Cyclo-stationary and Kurtogram are becoming very popular to detect the rotating machinery faults. However, these techniques become less effective in more complex system such as multi-stage gearboxes with many bearings [155].

Other state of art technique to extract fault frequencies from the recorded signal in rotating machinery is Minimum Entropy Deconvolution (MED) algorithm as demonstrated by Endo et al [156] or its variations such as Optimal Minimum Entropy Deconvolution (OMED) [157], Multipoint Optimal Minimum Entropy Deconvolution Adjusted (MO-MEDA) [158] or Maximum Correlated Kurtosis Deconvolution (MCKD) [158] algorithms.

In this section, a novel combinatorial signal processing technique based on intrinsic mode decomposition (IMF) method in conjunction with cyclic spectral coherence for detection of fault frequencies in real systems is proposed and is compared with MCKD technique. The used signal is recorded from the mock tidal turbine that was discussed in Chapter 5 in an imbalance condition. The recorded signal and calculated minimum entropy deconvolution signal is shown in Figure 7.23. Although the technique removed the noises from the signal, no obvious peak or cyclic behaviour is visible in the signal.

To analyse the new signal further, both short time Fourier transform and the Fourier transform of the signal calculated using MCKD was calculated and are presented in Figure 7.24. As it can be seen in the figure, no obvious signature from the fault is visible in the signal spectrum.

Calculating the cyclic spectral coherence of the recorded signal reveals 10.5 Hz cyclic frequency corresponding to the gear mesh frequency of the first stage (see Table 5.4) that suggests the imbalance condition of the gearbox. However, performing same calculation on the signal obtained using MCKD technique does not reveals any obvious fault frequency. This is shown in Figure 7.25.

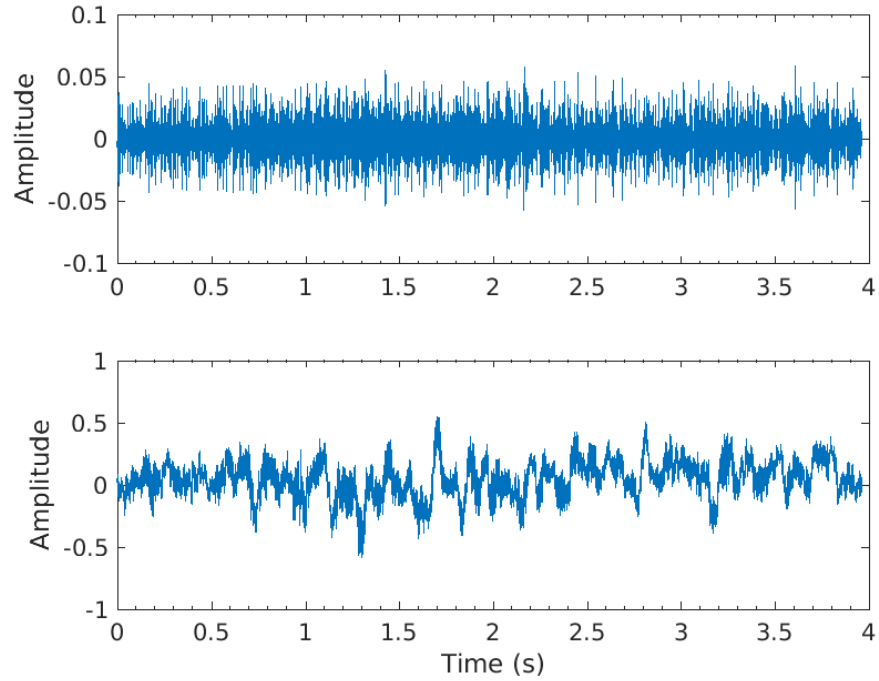


Figure 7.23: The vibration signal recorded from the mock tidal turbine with imbalanced condition at top and the calculated minimum entropy deconvolution using MCKD technique at bottom.

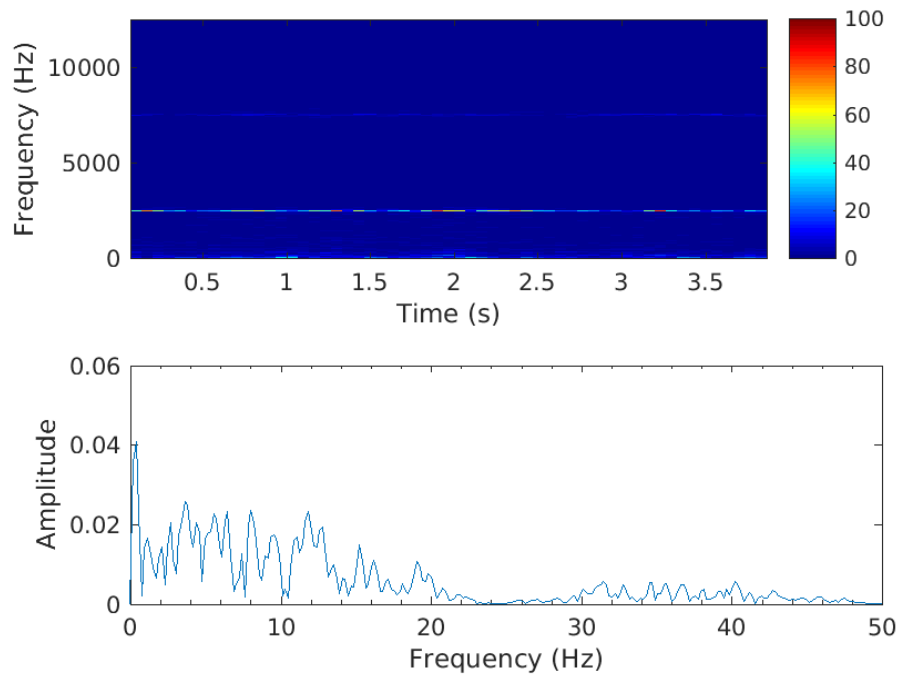


Figure 7.24: The short time Fourier transform (top) and spectrum (bottom) of the vibration signal recorded from the mock tidal turbine with imbalanced condition.

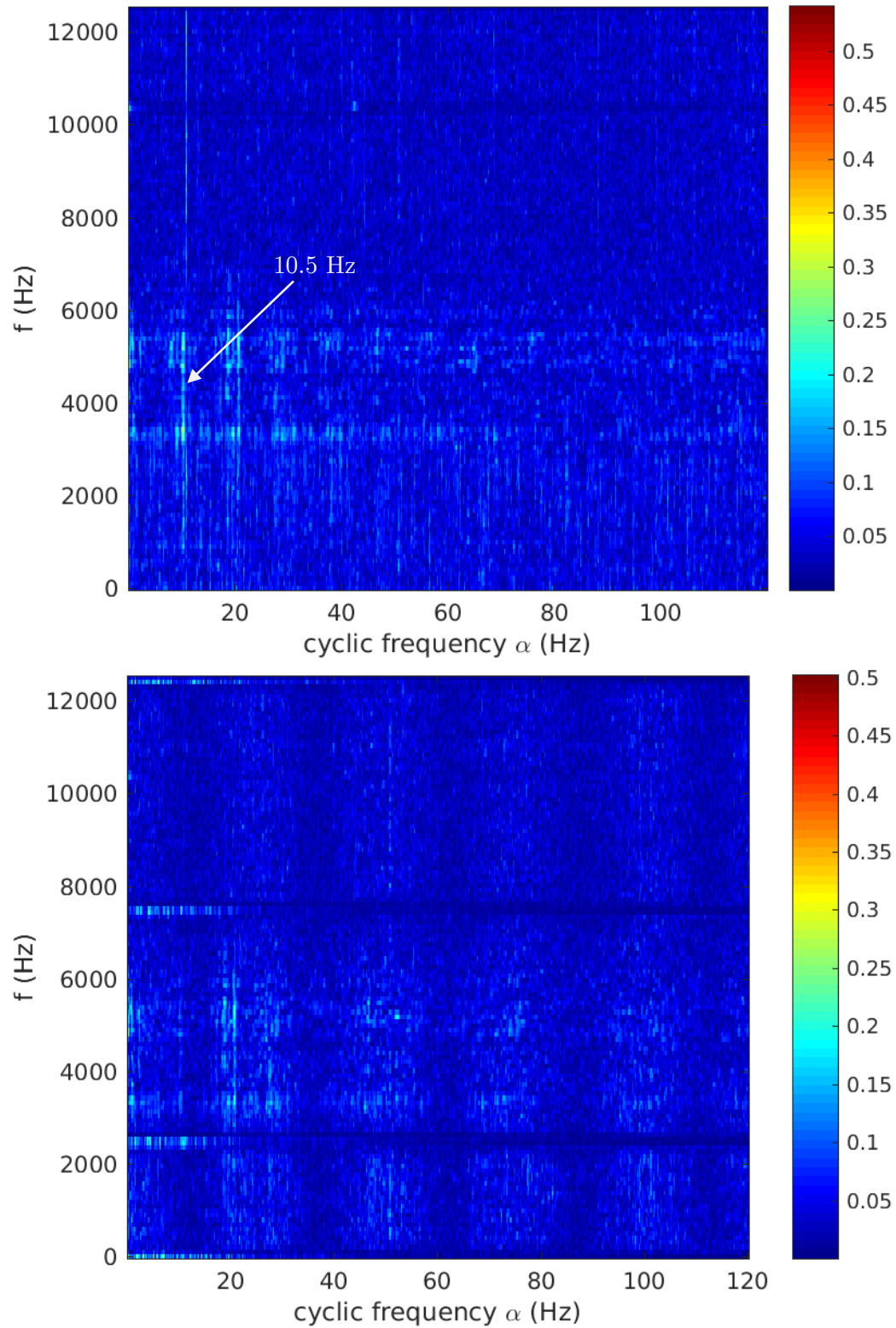


Figure 7.25: The cyclic spectral coherence calculated on vibration signal (top) and MCKD extracted signal (bottom) obtained from the mock tidal turbine with imbalanced condition

The same vibration signal was used to calculate the intrinsic mode functions (IMFs) of the signal using ensemble empirical mode decomposition technique (EEMD). Figure 7.26 shows the calculated IMFs. From the calculated IMF signals it is clearly visible that there are several periodic vibrations present in the time signal.

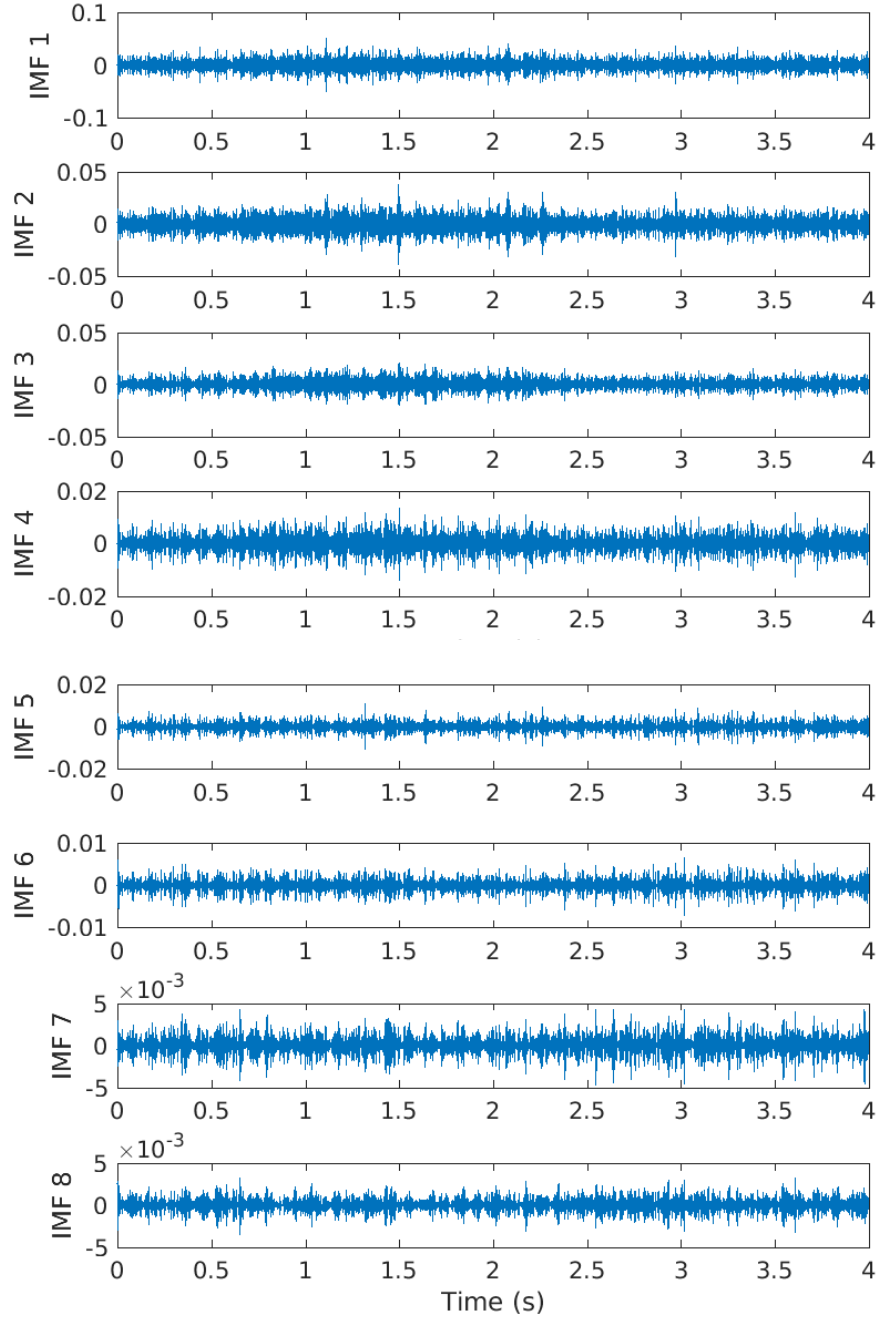


Figure 7.26: Calculated IMFs of vibration signal obtained from the mock tidal turbine with imbalanced condition.

Performing the cyclic spectral coherence calculation on each IMF reveals the fault frequency hidden in the vibration signal (Figure 7.27). The gear mesh frequency is clearly visible in the cyclic spectrum of the first IMFs (higher frequency IMFs) indicating the imbalanced condition.

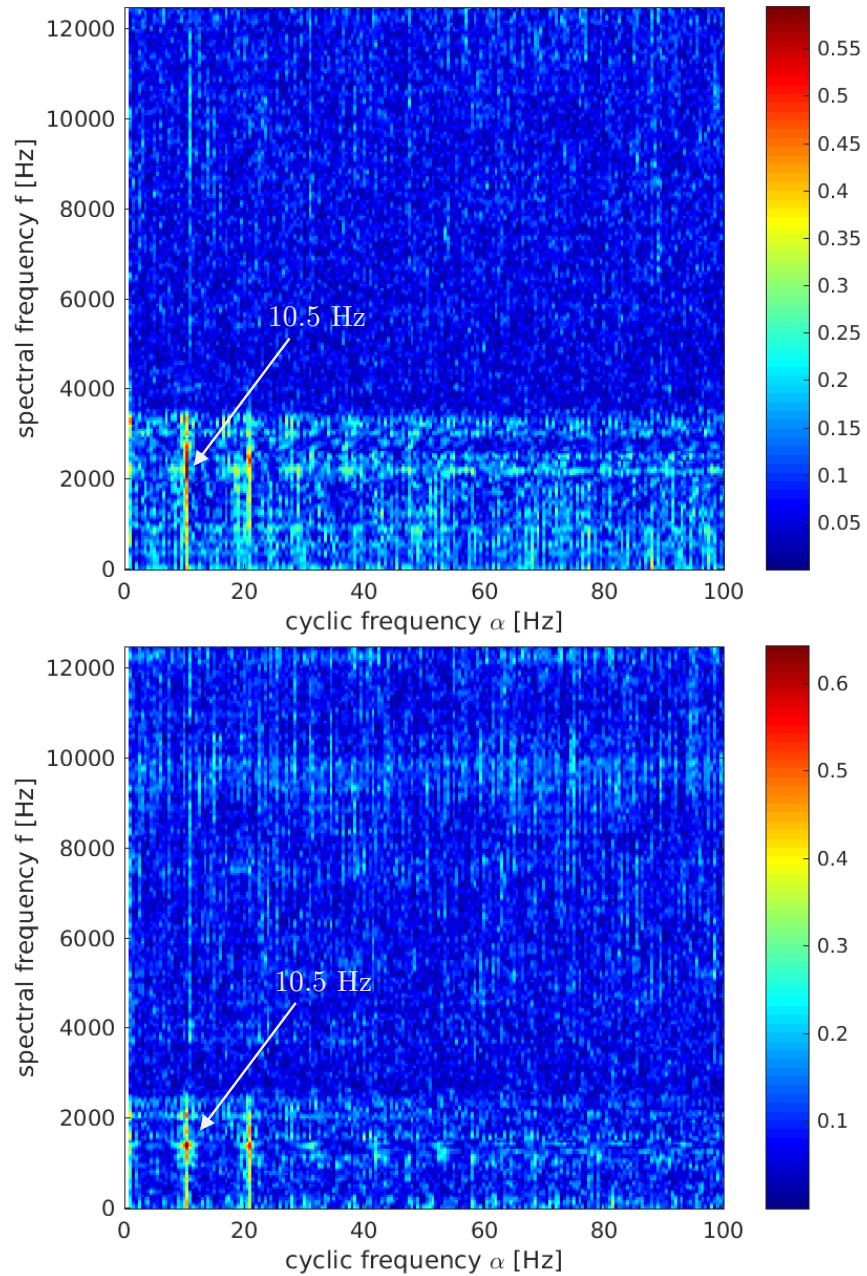


Figure 7.27: The cyclic spectral coherence calculated on the first (top) and second (bottom) IMFs of vibration signal obtained from the mock tidal turbine with imbalanced condition

The cyclic spectral coherence calculation of the higher IMFs (lower frequency) reveals the presence of 5.3 Hz GAPF frequency (see Table 5.4) in the signal that also indicates the imbalance condition in the system. This frequency was invisible to the other used techniques.

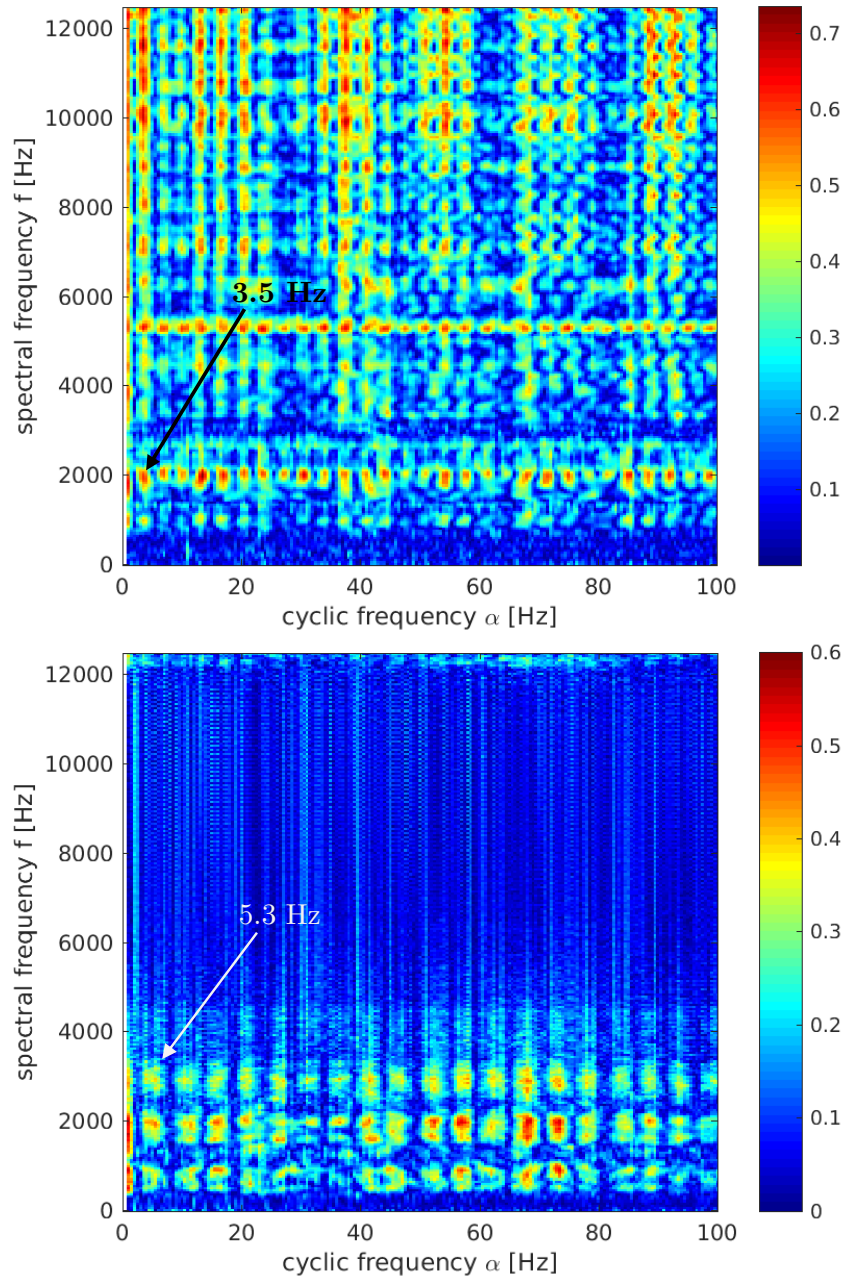


Figure 7.28: The cyclic spectral coherence calculated on the 6th (top) and 8th (bottom) IMFs of vibration signal obtained from the mock tidal turbine with imbalanced condition

In addition to the GAPF frequency, the second stage rotation frequency (3.5 Hz) is also becoming visible in the vibration signal after performing the cyclo-stationary analysis on the IMFs, as shown in Figure 7.28. The presence of both first stage gear mesh and GAPF cyclic behaviour clearly indicates the imbalance applied to the first stage. The existence of the second stage rotational frequency could as well indicate the imbalance. Nonetheless, it can also show the normal vibration contaminating the signal.

For comparison purposes, the analysis was also applied to the de-noised signal using the Wavelet de-noising technique. This was carried out using Daubechies-3 wavelet. After de-noising, the gear mesh frequency becomes more obvious compared to the raw signal, however, it also contaminate the Cyclic Spectral Coherence result as it is shown in Figure 7.29.

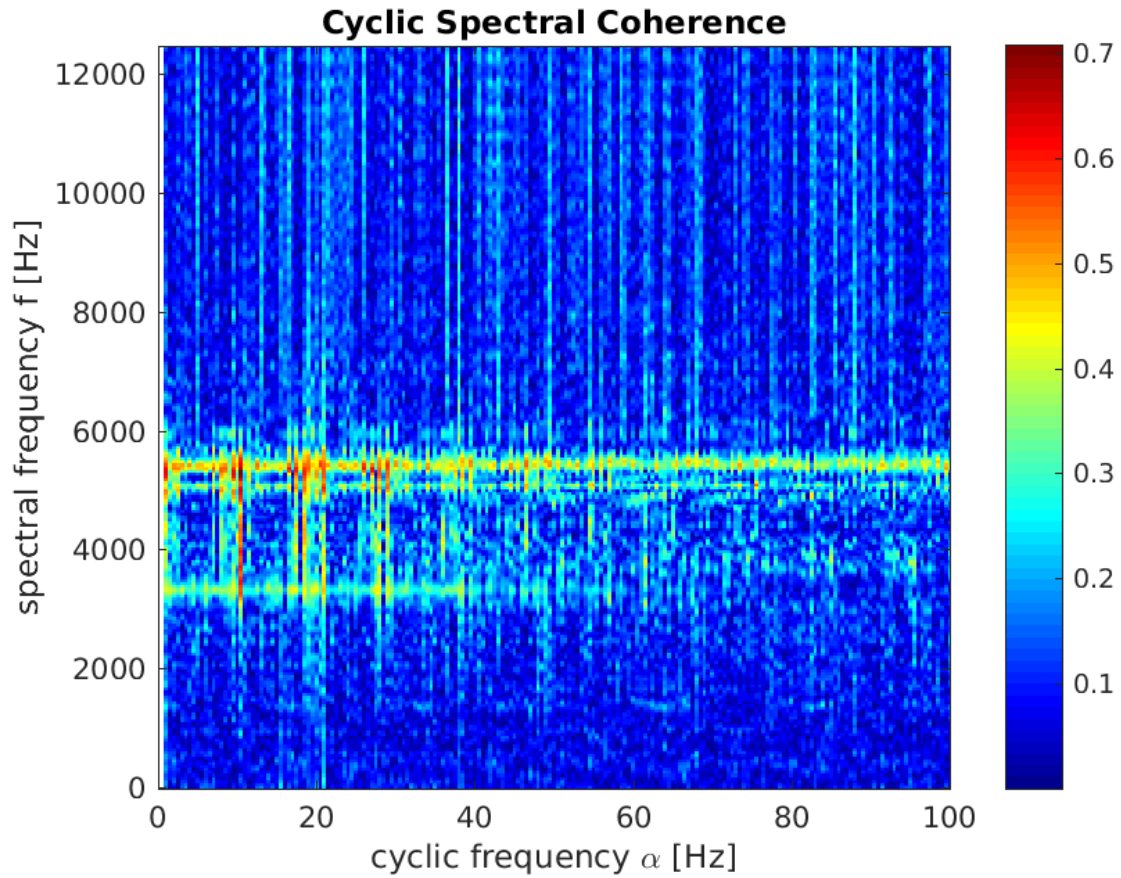


Figure 7.29: The cyclic spectral coherence calculated on the filtered signal using Wavelet Daubechies-3 (db3) filter obtained from the mock tidal turbine with imbalanced condition

A similar procedure was also applied to the vibration signal recorded from wind turbine M2. The signal recorded from planetary stage radial sensor was used in this analysis. Again, the signal obtained using MCKD was not very successful in revealing the fault frequencies as shown in Figure 7.30 but the combination of EEMD and Cyclo-stationary, successfully identified the planetary bearing fault frequency (BPFI) and enhanced the result by reducing the noise and artefact from gears as shown in Figure 7.31.

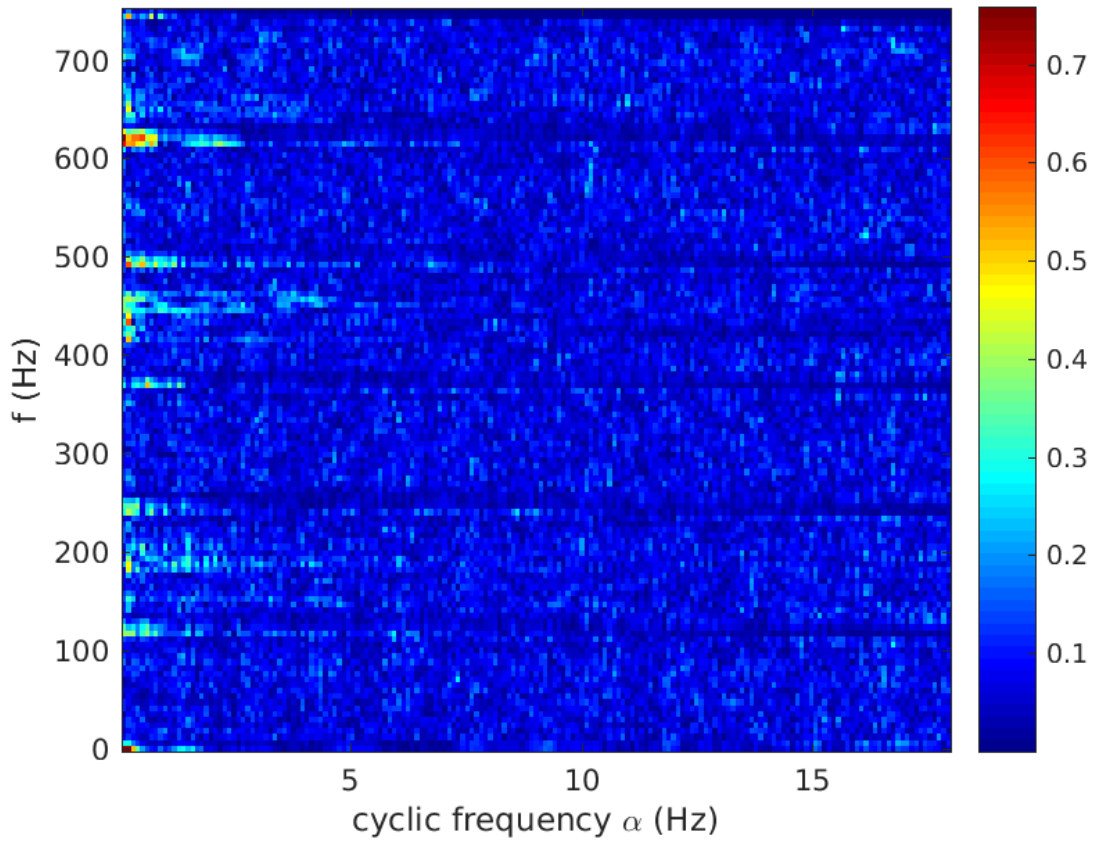


Figure 7.30: Calculated cyclic spectral coherence on the extracted signal using MCKD technique.

Looking at the higher frequencies for the planetary gear mesh, the improvement effect of IMF on the cyclic spectral coherence is considerably more as shown in Figure 7.32.

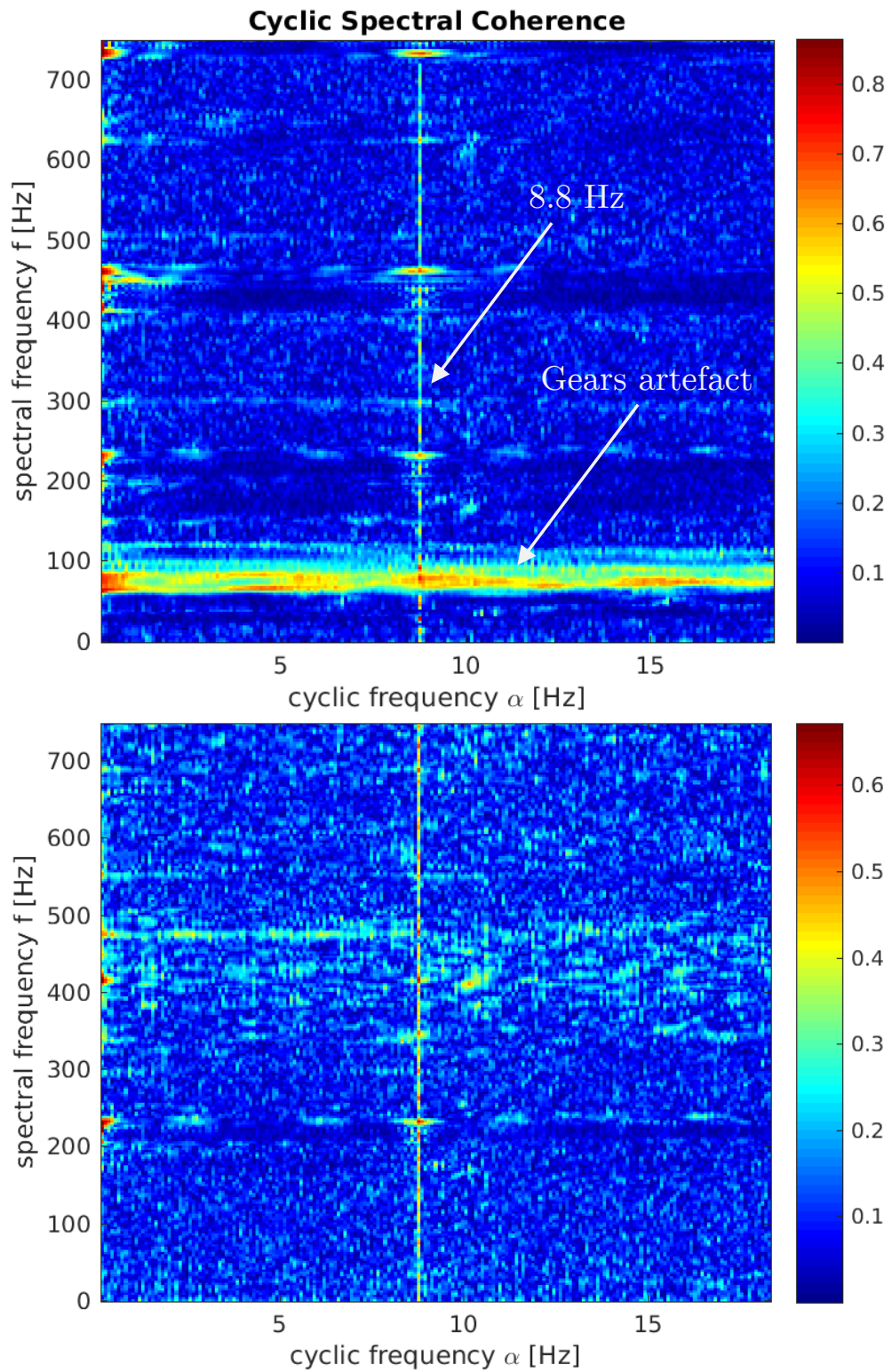


Figure 7.31: Calculated cyclic spectral coherence on the raw signal (top) and first IMF (bottom) of the signal, showing the planetary bearing BPFI frequency at 8.8 Hz.

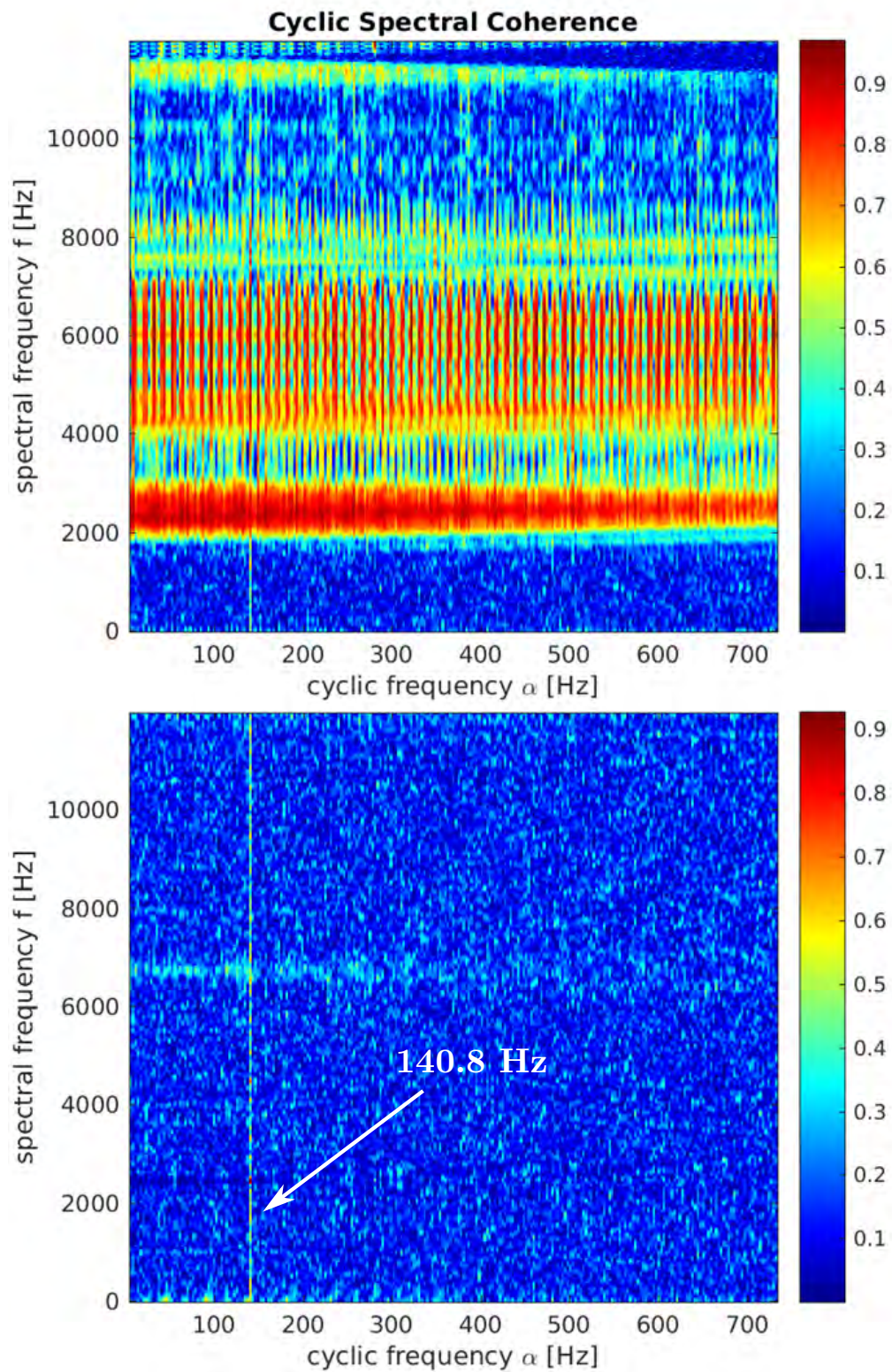


Figure 7.32: Calculated cyclic spectral coherence on the raw signal (top) and first IMF (bottom) of the signal, showing the planetary gear mesh frequency at 140.8 Hz

7.5 Summary

In this chapter, an automated signal processing software developed during this project to perform signal processing on large amount of data was introduced. Moreover, it was shown that it is possible to perform condition monitoring using SCADA data with the aids of machine learning techniques.

Advanced and more recent signal processing techniques can identify the faults in the system in earlier stage, however, some hidden faults are not easily detectable. A novel signal processing chain was proposed and evaluated to detect hidden faults in the gearbox of industrial wind and tidal turbines.

“Success is not final, failure is not fatal: it is the courage to continue that counts.”

— Winston Churchill

Chapter 8

Conclusion and future works

8.1 Summary

In this thesis various techniques and tools for condition monitoring of tidal and wind turbines were explored. Unlike most rotating machinery, wind and tidal turbines are facing an unpredicted and adverse operational environment. This renders very difficult the prediction of operational degradation and hence estimation of the lifespan of the system in order to accurately determine maintenance actions timely. Thus, the performance and reliability of tidal and wind turbines are strongly depending on dynamic condition monitoring and maintenance methods.

However, considering the number of wind turbines in a wind farm and the amount of data that has to be processed continuously, renders this task very challenging. Furthermore, the complexity of the used components such as the gearbox unit is making the condition monitoring of these closed units very difficult and challenging.

In this research the possibility of the detecting the fault in the gearbox system of the wind and tidal turbines at the early stages was investigated and it was shown that the faults in the gearbox are detectable using various signal processing techniques.

Both acoustic emission and vibration signals were considered to investigate the gearbox. It has been shown that the vibration and acoustic emission signals are complementary

to each other and cannot replace one another. Although most of faults are picked up using both types of sensors, there are certain conditions that only one of the sensors can detect or the sensors complement each other increase the reliability of the predicted condition.

Nevertheless, the acoustic emission signal requires higher sampling rate and is much larger than the vibration signal and can be used for quick snapshot diagnostics of the system health while the vibration signals can be monitored continuously due to smaller size and less computational requirement.

Although the traditional signal processing like FFT and RMS are very powerful and usually a good starting point to detect the fault in the system, in many cases, additional advanced techniques such as spectral kurtosis, Kurtogram demodulation or cyclo-stationary are required to identify and pinpoint the fault in the system. That being said, in complex systems with multiple wear and degradation, these advanced techniques are losing their ability to perform efficiently.

The intrinsic mode decomposition technique, although has been around for many years, and is very adaptive and efficient; it has not attracted much attention in the field of condition monitoring. In this thesis it was shown that the empirical mode decomposition technique can be used to remove random noises from the signal and condition the recorded signal. It was also shown that this technique used in conjunction of cyclo-stationary analysis is able to detect features that are invisible to most of advanced and state of the art signal processing techniques.

It was demonstrated that, using advanced machine learning techniques such as artificial neural networks, it is possible to reduce the amount of the recorded condition monitoring data and detect the faults with high prediction accuracy. However, more training and experimental data is required to improve the performance of such systems.

The majority of the signal processing in this research was performed using the MATLAB software that was developed during this research as a signal processing suite for condition monitoring and gearbox signal processing. Although this system is capable of detecting the fault frequencies and automatically analyse the data, still fine-tuning input

and judgement from signal processing experts is required to detect the fault. However, this tool will help the signal processing expert in performing all the calculations in one location and perform the desired processing over a large amount of data using define system configuration automatically.

8.2 Future works

The condition monitoring systems for offshore wind and tidal turbines are still in their development stages and have not matured yet. Obtaining actual signals recorded from offshore wind or in particular tidal turbines is difficult as these systems are not easily accessible.

At present, signal processing and condition monitoring of the systems relies on the knowledge and experience of the expert performing the condition monitoring and varies depending individual systems and there is a need for a more generalised condition monitoring system to be developed. Machine learning and classification techniques are shown to perform well in identifying the fault before happening, however, these systems require fine tuning and more research is required to optimise the feature selection.

This research provided an initial path showing the possibilities and tools to enhance and improve existing signal processing in offshore wind and tidal turbines and can be a starting point for various studies to improve the condition monitoring techniques for large scale and industrial wind and tidal turbines both onshore and offshore.

Appendix A

Publications

Book chapter

- Roshanmanesh, S. (2019). Tidal Turbines in *Non-Destructive Testing and Condition Monitoring Techniques for Renewable Energy Industrial Assets*. M. Papaelias, F. P. Garcia and A. Karyotakis. UK, Elsevier: Butterworth-Heinemann.

Journal articles

- Zhou, J., Roshanmanesh, S., Hayati, F., et.al. (2017) *Improving the reliability of industrial multi-MW wind turbines*, Insight–Non-Destructive Testing and Condition Monitoring Vol. 59 No. 4

Conference papers

- Jantara Junior, V., Zhou, J., Roshanmanesh, S., Hayati, F., et.al. (2017) *Evaluation of Damage Mechanics of industrial wind turbine gearboxes*, First World Congress on Condition Monitoring (WCCM 2017), London, UK
- Jantara Junior, V., Zhou, J., Roshanmanesh, S., Hayati, F., et.al. (2017) *Driving forward wind turbine industrial standards on gearbox materials, maintenance, remaining lifetime assessment and condition monitoring methodologies*, The 56th An-

nual Conference of The British Institute of Non-Destructive Testing (NDT 2017), Telford, UK

- Roshanmanesh, S., Hayati, F., et.al. (2016) *Drive-train condition monitoring for offshore wind and tidal turbines*, 2nd International Conference on Renewable Energies Offshore (RENEW 2016), Lisbon, Portugal
- Zhou, J., Roshanmanesh, S., Hayati, F., et.al. (2016) *Increasing the reliability of industrial multi-MW wind turbines*, The 55th Annual Conference of The British Institute of Non-Destructive Testing (NDT 2016), Nottingham, UK

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